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Sagit Bar-Gill
Erik Brynjolfsson
Nir Hak

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ABSTRACT

As more and more activities in the economy become digitized, analytics and data-driven decision-making (DDD) are becoming increasingly important. The adoption of analytics and DDD has been slower in small-to-medium enterprises (SMEs) compared to large firms, and reliable causal estimates of the impacts of analytics tools for small businesses have been lacking. We derive experiment-based estimates of the effect of an analytics tool on SME outcomes, analyzing the randomized introduction of eBay's Seller Hub (SH), a data-rich seller dashboard. We find that SH adoption is associated with increased DDD, and that access to SH increases e-retailers' revenues by 3.6% on average, as more items are transacted and service quality increases, without increases in average prices. Our results suggest that analytics and DDD help SMEs establish a competitive advantage. Managerial practices play an important role in reaping the benefits from the analytics dashboard, as over a third of the SH impact is driven by active performance monitoring. This suggests that digital platforms could increase revenues by supporting the adoption of analytics tools by SMEs. Furthermore, policies supporting small businesses' transition to the data era could address gaps in analytics and data-driven decision-making (DDD) by providing access to tools such as SH, as well as offering appropriate managerial training.

Sagit Bar-Gill
Tel Aviv University
sagitbargill@gmail.com

Nir Hak
Uber and Harvard
nirhak@gmail.com

Erik Brynjolfsson
Stanford Digital Economy Laboratory
353 Jane Stanford Way, Office 136
Stanford, CA 94305
and NBER
erik.brynjolfsson@gmail.com

1. Introduction

The volume of data available to support managerial decision-making is growing rapidly as firm operations become digitized. As a result, an increasingly-important challenge for managers has become extracting actionable insights from data – turning information to business value. To quote Peter Sondergaard, “Information is the oil of the 21st century, and analytics is the combustion engine.” Indeed, big data analytics and data-driven decision making, dubbed DDD, are recognized as increasingly important for managers in the data era (Brynjolfsson, Hitt, and Kim 2011; Brynjolfsson and McAfee 2012).

Nonetheless, despite the wide-spread interest in analytics and DDD, adoption has been concentrated in large firms, while small-to-medium enterprises (SMEs) are lagging behind (Brynjolfsson and McElheran 2016, Llave 2017). Evidence suggests that economies of scale contribute to this uneven adoption (Brynjolfsson and McElheran 2016). In particular, the high cost of acquiring and implementing analytics and big data tools may be a key driver of lower adoption rates of these tools by SMEs. Thus far, the extant literature has focused on the value of big-data analytics for large firms (Berman and Israeli 2022, Brynjolfsson et al. 2011, Brynjolfsson and McElheran 2019, Müller et al. 2018), whereas the benefits for SMEs remain underexplored for lack of appropriate data. We, therefore, set out to estimate the impact of analytics on SME outcomes, to inform small business managers’ investment decisions in analytics and DDD and fill this gap.

Drawing on a large-scale field experiment, this paper derives causal estimates of the impact of analytics and analytics-enhanced DDD on SMEs’ performance. We study the impact of an analytics dashboard on small-to-medium e-retailers’ sales on eBay, as well as on their pricing and quantities sold, new listing creation, and quality of service as captured by feedback scores. We further highlight the importance of managerial performance monitoring in driving these impacts.

We study the field experiment setting created by eBay’s staggered rollout of Seller Hub (SH), a new data-rich seller dashboard, initially targeted at B2C sellers. SH has been described as a “revolutionary tool” that “brings the power of the eBay data warehouse and the valuable insights that data offers, directly to sellers to help them manage and grow their business”.[1] Indeed, SH prominently displays performance reports highlighting conversions, page-views, and other selling metrics (Figure 1). In sellers’ own words, posted to the SH discussion board:[2] “*I can see how the additional information, such as, the number of impressions my items have received can be useful to me in determining whether or not my listing information is effective or needs to be improved in order to increase sales. I especially like the overview. I like being able to glimpse*

[1] See https://www.ebay.com/sh/landing and https://www.ebayinc.com/stories/news/ebays-seller-hub-now-live-for-all-u-s-sellers/.

[2] https://community.ebay.com/t5/Archive-Seller-Hub/bd-p/archivesellerhub/page/58.

at my listing activity to get a quick and instant idea of how things are going." This anecdote suggests that by offering easily accessible data and analytics, SH enables increased DDD.

SH was launched in 2016 using eBay's experimentation platform. A key feature of the roll-out was that randomly selected cohorts of sellers received access to SH in seven ramp-up stages. This randomization-based time-varying roll-out of SH allows for a causal identification of the analytics treatment effect, as we compare sellers with and without access to SH in a generalized difference-in-differences (DiD) setting (Angrist and Pischke 2009).

Notably, we study the impact of analytics and analytics-enhanced DDD on B2C sellers on eBay. These are largely small-to-medium retailers with annual sales on eBay between $10,000-$100,000 for the vast majority of our sample. We thus provide estimates for the impact of enhanced DDD on small-business outcomes.

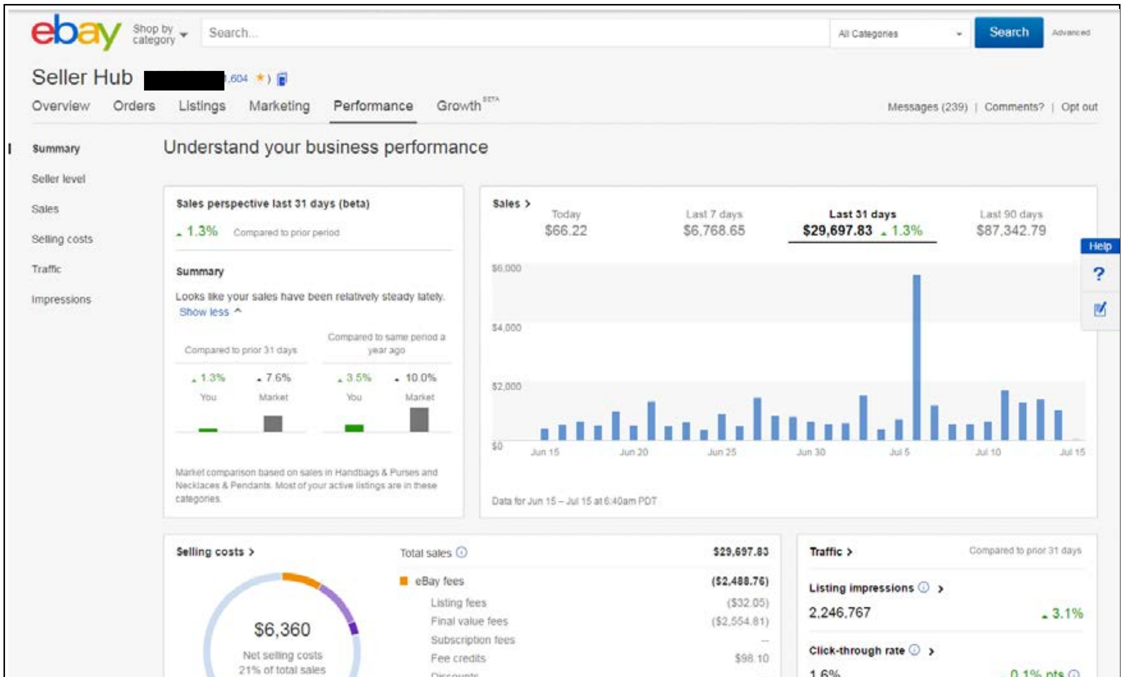

Figure 1. SH Screenshot.

First, to understand SH's role in increasing DDD for its adopters, we partnered with eBay's seller experience team to field a survey eliciting reported DDD components (e.g., availability of data for decision making, data use, and performance monitoring) – currently and in the year preceding SH's roll-out. We examine the relationship between changes in DDD and SH adoption, finding a strong positive relationship between SH adoption and increases in DDD. We thus consider SH as a DDD-enhancing tool, and SH's launch as an analytics and DDD treatment. Hereinafter, we use DDD to mean analytics-enhanced DDD.

We proceed to study the causal impact of SH, using a generalized DiD specification, where the outcomes of ramp-up groups with and without access to SH are compared in weeks before and after they are granted access to SH. We find that access to SH leads to a 3.6% increase in weekly sales on average. This is an intent-to-treat (ITT) estimate, as sellers were randomly invited to use SH, but actual adoption was based on self-selection. We further examine the effect of treatment-on-the-treated (TOT), using the opt-in invitation as an instrument for SH adoption. Our TOT estimate suggests that SH adoption leads to a 12.5% increase in weekly sales, on average. This serves as an upper bound of the SH impact and the ITT estimate serves as a lower bound.[3]

These results are strengthened by a relative time model studying the dynamic impact of SH access on weekly sales revenue. We find a positive effect of 2.5-3.6% in the first three weeks following ramp-up, increasing to 4.4-5% in weeks 4-5, and to 6.1-7.7% from week 6 onwards. Our analysis confirms that there are no pre-treatment differences in the sales trend between ramp-up groups thereby validating the parallel trends assumption underlying our DiD empirical strategy.

Decomposing the DDD impact on sales, we find that the increase in sales is driven by increases in the quantity of items sold, rather than by price. The increase in quantity sold is enabled by increased new listing creation, and further driven by increases in service quality as captured by sellers' feedback scores. As examples of how SH-enhanced DDD may lead to these effects, we note that improved demand tracking via SH's traffic report can help adopters respond faster to changes in demand compared to competitors, and tighter monitoring of seller level reports can help sellers better maintain a high standing, which affects their listings' ranking in search results.[4] Hence, in both examples, improved information and enhanced monitoring through SH allows adopters to sell larger quantities than their competitors, without lowering their average prices.

Comparing SH impacts in homogeneous and differentiated product categories, we find that the benefits of SH are larger for sellers who sell mostly in homogeneous product categories, where product differentiation is lower. Moreover, while SH does not affect pricing on average, it does allow sellers in homogeneous product categories to increase their prices. These analyses suggest that access to information via SH drives service differentiation and strengthens competitive advantage, in line with classical arguments regarding the effects of information (e.g., Porter and Millar 1985).

Following previous work that highlighted the complementarity between IT and managerial practices (e.g., Bharadwaj et al. 2007, Bloom et al. 2014, Devaraj and Kohli 2003), we investigate the role of managerial monitoring of performance reports in driving the benefits from SH. We find that over a third of the impact of SH access is driven by active performance monitoring. These results suggest that the DDD treatment

[3] See discussion of the TOT estimation in Section 4.
[4] Along with other factors, see https://www.sellbrite.com/blog/ebay-sales-conversion-rate/.

created by SH is more effective for sellers with high levels of performance monitoring.

This work contributes to recent efforts quantifying the impact of analytics and DDD on business performance. Our causal estimates of the positive impacts of an analytics dashboard for small businesses suggest that SMEs may benefit from higher adoption rates of analytics and big data tools, and offer a necessary input for small business managers' investment decisions in data assets and analytics tools and capabilities.

For managers of digital platforms, our results suggest that platforms will benefit from embedding analytics tools to support SMEs, as these would increase the revenue of small businesses on the platform and further make the platform more attractive to new entrants, leading to higher platform revenues from both existing and new SMEs on the platform. For policy makers, our estimates may serve to assess whether SMEs' adoption of analytics and DDD is suboptimal, and guide decisions to subsidize analytics solutions for SMEs by small business authorities.[5] Furthermore, we demonstrate that managerial monitoring practices drive effective DDD. This is instructive for both managers of small businesses and for policy makers who can improve small businesses' growth and survival in the data era with appropriate training.

Finally, our unique setting of a randomization-based roll-out of a DDD-enhancing tool allows us to derive causal, experiment-based estimates of the effects of analytics and DDD on firm outcomes. These estimates provide an important corroboration of previous estimates of the impacts of IT, information, and analytics that were based on quasi-experiments (e.g., Aker 2010, Jensen 2007), and on econometric analyses of observational and survey data (e.g., Berman and Israeli 2020, Brynjolfsson and McElheran 2019, Overby and Forman 2015).

2. Related Literature

Studying the effects of data and analytics on small e-retailers, this paper relates to the literature on the impacts of information and information technologies (IT) on firms and markets, and to more recent studies on the impacts of data and analytics in different business and market settings.

2.1 The Impacts of IT and Information on Firms and Markets

The growing use of IT in the 1980s and 1990s motivated the study of the link between investments in IT and firm performance and productivity. Early empirical work was unable to identify a positive effect of IT on firm productivity, widely referred to as the "productivity paradox of IT" (Brynjolfsson 1993). This paradox was resolved, when subsequent research employing larger and more up-to-date firm-level datasets found strong and significant effects of IT investments on firm productivity (Barua et al. 1995, Brynjolfsson

[5] SME managers and policy makers should, of course, weigh the estimated benefits against the costs of investments in analytics tool or related subsidies. Benefits are likely to outweigh costs, as low-cost analytics tools for SMEs have become widely available; e.g., https://www.scoro.com/blog/best-business-intelligence-tools-for-small-businesses/.

and Hitt 1996, Cardona et al. 2013).

These results paved the way for a stream of work studying the impacts of different types of technologies and information on firms and markets. Early work on the effects of the internet on marketplaces discussed the internet's role in matching buyers and sellers, lowering transaction costs and creating more efficient markets (Bakos 1998). Brynjolfsson and Smith (2000) provided initial evidence of lower prices and reduced frictions in e-commerce. Positive effects of enterprise resource planning (ERP) and supply chain management (SCM) systems on firm profits were documented by Hendricks et al. (2007), and a longitudinal study by Hunton et al. (2003) suggested that adopters gained a competitive advantage over non-adopters. Jensen (2007) and Aker (2010) studied the impact of mobile telephony rollouts on fish and grain markets, finding that this technology increases profits, while reducing prices and price dispersion.

Empirical evidence stressing the role of information and its impacts on a range of firm decisions developed concurrently, and in the 2010s. Price information on price comparison sites was found to decrease prices (Brown and Goolsbee 2002). Access to real time pricing data via a webcast channel was found to affect buyers' and sellers' decisions about where to buy and sell cars, and to lower price dispersion (Overby and Forman 2015), further supporting market efficiency by surfacing information on arbitrage opportunities (Subramanian and Overby 2017). Providing daily pricing information via text-messages in rural agricultural markets was similarly found to reduce geographic price dispersion "over and above access to mobile phone technology and other means of communication" (Parker et al. 2016). Information on the identity of winning bidders in a B2B auction setting was shown to facilitate other bidders' learning, leading to declining prices in subsequent bidding rounds (Lu et al. 2019).

Sharing our focus on SMEs, several of the above-mentioned papers studied IT and information impacts on small businesses (e.g., Aker 2010, Jensen 2007, Overby and Forman 2015), yet they largely estimated effects on pricing and supply patterns. We thus contribute to these studies by estimating the effects of analytics on a rich set of seller metrics, from feedback scores representing customer satisfaction to pricing, quantities sold and listing activity, in addition to the main effect on revenue, providing a comprehensive view on the impacts of analytics on SMEs. Furthermore, we study the impacts of an analytics dashboard, rather than technology adoption or access to specific information, and therefore relate to the stream of work that extended the study of the effects of IT and information into the big data era, by focusing on the impacts of big data and analytics.

2.2 The Impacts of Big Data and Analytics on Firms, and Heterogeneity by Firm Size

In the 2010s, with the growing attention to big data, researchers continued to study the impact of technology and technology-enabled data access, with a stronger focus on the impacts of analytics and data-driven decision making (DDD). Indeed, between 2005 and 2010 the adoption of DDD in US manufacturing had nearly tripled (Brynjolfsson and McElheran 2016). Case and survey-based evidence pointed to a strong association between the use of analytics and firm growth rates (Davenport and Harris 2007), and showed that top-performing firms invest substantial amounts of their technology expenditure in analytics, practicing high levels of DDD (Simchi-Levi et al. 2015). Theoretically, improved decision-making due to larger data assets and analytics capabilities has been viewed as an important mechanism driving the effect of data on firm performance (Mithas et al. 2011, Sharma et al. 2014).

As data becomes increasingly abundant, gleaning the right insights from big data becomes the main challenge for managers – "It's not the size of the data – It's how you use it" (Pauwels 2014), and recent studies in various fields of inquiry have been exploring the impact of big data analytics and DDD practices, rather than focusing on the impact of raw data or specific information. The finance and accounting literatures have discussed the importance of big data analytics in financial statement audits (Cao et al. 2015), banking, financial services and insurance (Ravi and Kamaruddin 2017), and supply chain finance (Yu et al. 2021).

In the marketing literature, recent work has studied the effects of big data and DDD in retail, showing that investments in advanced analytics for improved decision making are associated with supra-normal profits, based on a meta-analysis combined with a survey (Bughin 2016). Germann et al.'s (2013, 2014) survey-based work further points to the performance benefits of using marketing analytics tools, the importance of an analytics-driven culture, appropriate data, and IT support, as well as to under-investment in analytics by retailers. Moreover, a recent field study (Bradlow et al. 2017) has shown that predictive analytics-driven price optimization improved gross margins at a US retail chain.

In healthcare, data dashboards and DDD have been shown to improve providers' performance and quality of care (Khairat et al. 2018, Simpao et al. 2014). Recently, evidence from COVID-19 care demonstrates their importance in supporting clinical decision making regarding the prioritization of care and the allocation of scarce resources (Ibrahim et al. 2020).

Closely related to our work are recent studies in the information systems and marketing literatures focused on measuring the impacts of analytics and DDD on firm outcomes. Studying survey data from publicly traded firms, Brynjolfsson et al. (2011) find that DDD is associated with 5-6% improvements in productivity. More recently, Müller et al. (2018) find that, in a sample of large firms, using an enterprise analytics software supporting DDD leads to a 3% increase in productivity. Furthermore, a large-scale study of DDD in US manufacturing finds that frontier DDD is associated with 4-8% increase in productivity (Brynjolfsson and McElheran 2019). Finally, adoption of a retail analytics dashboard is found to increases e-commerce sites' revenues by 4-10% (Berman and Israeli 2022). Overall, these papers estimate impacts of analytics and DDD on firm productivity and performance of 3-10%, based on observational and survey data of large firms.

With these estimates representing analytics impacts in large firms, and considering the adoption lags of analytics tools in SMEs (Brynjolfsson and McElheran 2016, Llave 2017), we note that differential returns of IT investments by firm size have been studied in the IS literature. Such differential returns have been demonstrated mostly within large publicly traded firms (see Dedrick et al. 2003 for a survey). More recently, Tambe and Hitt (2012) compare returns in large versus medium-sized firms, finding substantially lower IT returns in midsize firms than in Fortune 500 firms. Angle and Forman (2018) compare IT returns across an even wider range of small to large manufacturers, finding that small plants see no returns to IT adoption, on average. More encouragingly, Jin and McElheran (2018) find that adoption of cloud computing by young firms is associated with higher survival and growth rates, suggesting that cloud-based IT offers new opportunities that are more suited for SMEs than traditional IT investments, which were characterized by economies of scale.

We therefore add to this body of work by estimating the impacts of analytics for SMEs. Our experiment-based estimates are of similar magnitudes to those found for large firms, adding robustness to prior estimation, while further contributing to the assessment of the efficiency of analytics adoption in SMEs (Brynjolfsson and McElheran 2016, Llave 2017). Moreover, our results may better serve to inform SME managers' decisions to invest in data and analytics, and are in the spirit of Jin and McElheran's (2018) findings on cloud computing – suggesting that simpler and less costly IT and analytics solutions may be especially important for SMEs, generating substantial gains and helping them catch up with larger competitors. Our findings may also be useful for policy makers, as they suggest that subsidizing DDD tools may be a very cost-effective form of aid that small business authorities can offer.[6]

Methodologically, our experimentally-derived estimates of the impacts of analytics and enhanced DDD further contribute to previous work on the impacts of IT, information, and analytics, in which causal estimates were based on the analysis of quasi-experiments (e.g., Aker 2010, Jensen 2007) and on econometric methodologies applied to observational and survey data (e.g., Berman and Israeli 2020, Brynjolfsson et al. 2021, Overby and Forman 2015). A randomization-based approach is considered the gold-standard for causal evidence and our access to the randomized roll-out of the SH dashboard is a unique feature of our setting. As a result, the estimates we derive add robustness to previous measurements reported in the literature (Angrist and Pischke 2010, Rubin 2008).

[6] See Appendix A6 for a comparison of our results to estimates of the impacts of small business authorities' programs supporting SMEs.

3. Background

SH is a tool for eBay sellers introduced in 2016. It is designed as a dashboard providing access to common selling activities, such as listing items, managing inventory and orders; it also offers performance reports and data-based recommendations for increasing seller revenue and efficiency. In SH, eBay took a significant first step towards providing its sellers with smart tools that build on eBay's vast data, and powerful reporting that can improve sellers' ability to monitor their business performance.

3.1. SH Design and Features

The SH dashboard is organized around six tabs: Overview, Orders, Listings, Marketing, Performance, and Growth. We hereby describe each tab, highlighting the new features introduced, as well as pre-existing functionality that has become part of SH.[7]

The Overview tab is the landing page for the SH tool, and as such is the most prominent new feature introduced by SH. It provides sellers with an overview of their eBay business performance in the form of graphs and summary information, while highlighting action items from other tabs, such as communications with buyers, items awaiting shipment, and the processing of returns. The Overview tab brings to sellers' attention several important reports that are also available in the Performance tab,[8] including: (1) Sales report – graphical presentation of dollar sales over a customizable period of time, additionally showing total amounts for the previous 7, 31 and 90 days, along with percentage changes relative to the previous period; (2) Traffic report for the trailing month showing total listing impressions, click-through rates, page views and sales conversion rates, along with percentage change from the month prior; (3) Feedback report for the trailing month showing the number of positive, neutral and negative feedback instances, along with the most recent feedback left by buyers; and (4) Seller level report showing current seller level, the upcoming evaluation date, and the expected level based on up-to-date customer service metrics. This information-rich gateway to eBay selling holds the main promise of SH, as it is designed to deliver business-relevant data and reports even to sellers who do not actively seek them in the Performance tab.

The Orders and Listings tabs provide all functionalities of creating listings and handling orders post-sale. Importantly, selling activities accessed via the Orders and Listings tab are essentially unchanged from pre-SH eBay selling, as SH replaces both My eBay/Selling, the basic free selling interface that serves mostly non-business sellers, and Selling Manager, the free selling tool for small and medium business sellers.[9]

[7] Screenshots and additional information on SH are available at https://www.ebayinc.com/stories/news/ebays-seller-hub-now-live-for-all-u-s-sellers/.

[8] We describe the default view. As most other eBay dashboards, the Overview tab is customizable, allowing sellers to rearrange, add or remove reports and modules.

[9] The latter's enhanced version, Selling Manager Pro, remains an add-on monthly subscription service, including additional features, such as richer automation rules for listing and relisting items, automated feedback, and custom

The Marketing tab is the action-center for sellers who have an eBay Stores subscription, and thus brings into SH all activities carried out by Store subscribers. These include creating and managing promotional offers and discounts and setting and monitoring advertising campaigns on the eBay platform. Placing these pre-existing functionalities within SH highlights eBay's focus on professional and business sellers in the design of SH.

The Performance tab provides customizable performance reports and data, endowing sellers with much improved monitoring capabilities. In addition to the reports originating from the Performance tab that are highlighted in the default Overview tab, discussed above, the tab further offers raw downloadable sales data, and a customizable selling costs graph tracking costs of selling on eBay (namely, fees and shipping labels) over time.

Finally, the Growth tab provides sellers with data-based insights and recommendations for growing their business. Pre-SH, recommendations on listing optimization were available via My eBay/Selling or via Selling Manager. In SH's Growth tab these recommendations are more easily accessible and have been enriched with competitive guidance. The Growth tab thus includes suggestions on how to increase listings' conversion rates for underperforming listings, as well as comparisons to similar listings on dimensions such as price, item condition and shipping cost. In the timeframe of our analysis the Growth tab was in Beta mode and was later updated to include additional types of insights.

Summarizing, SH consolidates eBay's selling tools into a single convenient dashboard, while placing data, reports and recommendations front and center. Indeed, eBay webpages describing SH and other promotional materials emphasize "more data" as a key feature of SH. Following its launch in 2016, studied in this paper, eBay has continued to improve the analytics and functionality of SH, providing additional benefits to sellers.

3.2. Seller Hub's Roll-Out

SH was debuted in September 2015 at eBay's 20th Anniversary seller event in San Jose. At that point, eBay began testing the product with a group of sellers, who volunteered to participate in the final steps of refining SH. In May 2016, when SH was deemed ready to be rolled out on a larger scale, eBay chose to gradually ramp-up its user base, focusing on eBay's business sellers.[10] Between May 12th and July 26th sellers were invited to opt-in to SH via email sent on one of six invitation dates, yielding six *ramp-up groups*. Sellers were assigned to ramp-up groups by eBay's experimentation platform, based on the last 2 digits of sellers' hashed user ID (i.e., the hashed user ID modulo 100), henceforth, *uid_mod*. On August 8th 2016, the ramp-up concluded with all US-based business and professional sellers receiving an email inviting them to opt-

sales reports.

[10] Business sellers are sellers whose annual sales revenue is at least 10,000 USD generated by at least 100 transactions.

in and begin using SH. This process yielded the following ramp-up groups: (1) May 12 – 6,301 sellers with *uid_mod 00-02*; (2) May 19 – 6,016 sellers with *uid_mod 03-05*; (3) June 6 – 13,213 sellers with *uid_mod 06-12*; (4) June 13 – 54,896 sellers with *uid_mod 13-40*; (5) June 21 – 38,049 sellers with *uid_mod 41-60*; (6) July 26 – 9,444 sellers with *uid_mod 61-65*; (7) August 8 – 56,303 sellers with *uid_mod 66-99.*

Assignment to ramp-up groups based on *uid_mod* is equivalent to randomization-based assignment. Therefore, the roll-out of SH created an experiment with a staggered treatment design.

3.3. Confirming Seller Hub's DDD Impact

We first establish that SH adoption is indeed associated with increased DDD. We worked with eBay's seller experience team to design a survey aimed at examining sellers' management practices, and how these may have changed following the introduction of SH. eBay fielded the survey in November 2016, with 304 responses collected from business sellers, 163 SH adopters and 141 non-adopters. Survey respondents all belong to the Entrepreneurs segment of B2C sellers – small commercial sellers with annual sales between \$10,000 and \$120,000; sellers from this B2C segment comprise 89.7% of our larger panel data.[11] Survey respondents are representative of Entrepreneurs in our panel data.[12]

Survey questions focused on DDD were designed to parallel the DDD section of the Census Bureau's Management and Organizational Practices Survey (MOPS), a new supplement to the Annual Survey of Manufacturers, analyzed in Brynjolfsson and McElheran (2016, 2019). As in the MOPS, sellers were asked to rate the availability of data to support decision making, data use for decision making, and performance monitoring practices, represented by the number of key performance indicators (KPIs) tracked, both at the time of the survey, as well as a year prior (see Appendix A1).[13] This allows us to compare changes in data-related management practices between users and non-users of SH. Furthermore, sellers reported their store characteristics, such as number of employees and locations, managers' education, and selling in non-eBay channels. Sellers additionally reported their avenues for learning about eBay selling and their preferred format for store performance data (verbal, quantitative, or a combination of both).

Analyzing survey responses, we observe larger increases in average reported data availability and use for managerial decision making for adopters relative to non-adopters over the year of SH's introduction. Furthermore, adopters report monitoring more performance metrics on average, with a larger increase in

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[11] Entrepreneurs were the target segment for the survey as eBay policy precludes sending out seller experience surveys to larger B2C sellers.

[12] The average annual sales for survey respondents in 2015 and 2016 are \$31,425 and \$26,745.12, and the average annual sales for Entrepreneurs in our panel are \$31,264 and \$25,810. T-tests comparing these means do not reject the null hypothesis of equal means in 2015 (p=0.9131) and in 2016 (p=0.6262).

[13] A similar post-hoc design was employed in the DDD section of the MOPS, accessible at https://www.census.gov/programs-surveys/mops/technical-documentation/questionnaires.html.

average reported monitoring intensity compared to the year prior relative to non-adopters (Figure 2).

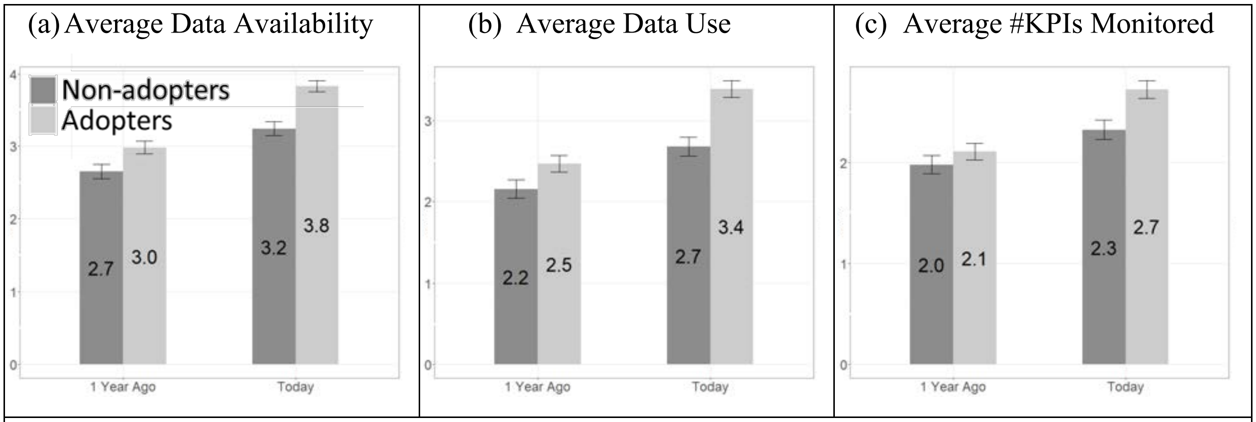

Figure 2. SH Adoption and Changes in Average Reported DDD Components. Comparing average current level to one year ago (prior to the SH launch), SH adopters (light gray) vs. non-adopters (dark gray), for: (a) Data Availability; (b) Data Use; (c) Number of KPIs monitored.

Following Brynjolfsson and McElheran (2016, 2019), we construct two measures of DDD, the *DDD Indicator* and the *DDD Index,* based on three DDD components – availability of data to support decision making, data use for decision making, and intensity of performance monitoring as represented by the number of key performance indicators (KPIs) monitored.[14] The *DDD Indicator*, denoted $\mathbb{I}_{DDD}$, is a binary variable that equals 1 for respondents reporting high data availability and use (responses in the top 2 categories), as well as high monitoring extent (the top category: tracking at least 5 KPIs).[15] The *DDD Index*, denoted DDD, is the sum of normalized responses to these three DDD-related questions, scaled to the [0,10] interval. For example, a seller reporting having a moderate amount of data available to support decision making (the middle category of data availability, coded as 3 out of 5), using data for managerial decisions 41%-60% of the time (the middle category of data use, coded as 3 out of 5), and tracking 1-2 KPIs (the second category of performance monitoring, coded 2 out of 4) will have $\mathbb{I}_{DDD} = 0$ and $DDD = 4.44$. On the other hand, a seller reporting having a great deal of data available (the fourth category of data availability, coded as 4 out of 5), using data for managerial decisions 81%-100% of the time (the fifth category of data use, coded as 5 out of 5), and tracking 5 or more KPIs (the fourth category of performance monitoring, coded 4 out of 4) will have $\mathbb{I}_{DDD} = 1$ and $DDD = 9.17$.

[14] Brynjolfsson and McElheran (2016, 2019) include a fourth DDD component—monitoring a combination of short-term and long-term production targets, as representing advanced performance monitoring. In our small survey sample, reports of a combined approach to target setting had a very low correlation with reports of high data availability ($\rho = 0.02$) and use ($\rho = 0.03$), such that the inclusion of this component in the DDD metrics did not yield statistically significant results. This component is viewed as less relevant for eBay sellers compared to the managers of large manufacturing plants studied in Brynjolfsson and McElheran (2016, 2019).

[15] The number of response categories for each survey question, as well as the definition of the DDD Indicator based on the top two categories for data availability and use, and on the top category for monitoring is aligned with Brynjolfsson and McElheran (2016, 2019), for comparability.

Overall, 3.95% of our 304 survey respondents had $\mathbb{I}_{DDD} = 1$ in the year prior to taking the survey (based on the retrospective survey items), and the average DDD index was 3.79. At the time of the survey, when the roll-out of SH had concluded, 12.83% of our respondents had $\mathbb{I}_{DDD} = 1$ and the average DDD index was 5.56. Our respondents are comprised of 163 adopters of SH and 141 non-adopters. We find that 4.91% of adopters had $\mathbb{I}_{DDD} = 1$ in the year prior, nearly quadrupling to 19.02% post SH, compared with 2.84% of non-adopters in the year prior, increasing to 5.67% after the SH roll-out. Similarly, the average DDD index for adopters increased from 4.11 to 6.27, compared with an increase from 3.43 to 4.74 for non-adopters.[16] We formally test the relationship between SH adoption and the change in DDD using the following model specification:

$$(1)\ \ DV_i = \alpha + \beta \cdot dSH_i + \epsilon_i$$

Where DV_i is one of $\{d\mathbb{I}_{DDD}, \Delta DDD\}$. The dependent variable $d\mathbb{I}_{DDD}$ is a binary variable that equals 1 if seller i's DDD indicator increased from 0 in the year prior to a current value of 1, and 0 otherwise. The dependent variable ΔDDD is the change in the value of the DDD index relative to the year prior. The variable dSH_i indicates SH adoption status (at the time of the survey) and is therefore 1 for adopters and 0 for non-adopters; α is a constant term, and ϵ_i is the idiosyncratic error term. Furthermore, 260 (out of 304) respondents reported their store and seller characteristics,[17] including measures for business size, formal education, learning practices and preference for quantitative over verbal information. These are listed in the Appendix (Table A2.1) and are added as additional controls to the main specification above.

The results (reported in Table 1) point to a positive and statistically significant association between SH adoption and increased DDD. Namely, SH adopters are 348% more likely than non-adopters to become data-driven decision makers, as represented by $d\mathbb{I}_{DDD} = 1$ (col. (1)), and this result strengthens when we include additional controls for seller and store characteristics in the specification (in col. (3), rising to 390%). Examining changes in the DDD index, we find that SH adoption is associated with a larger increase in DDD from the year prior, of an additional 0.85 index points (col. (2); the average index was 3.79 in the year prior). This increase in DDD is lower yet remains statistically significant, at 0.72 index points, when we control for seller and store characteristics (col. (4)). Based on this manipulation check, we conclude that SH's randomization-based launch can indeed be regarded as a DDD enhancing treatment.[18]

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[16] Note that baseline levels as well as the trend of DDD is positive for both adopters and non-adopters. This is likely due to awareness of Big Data and analytics, and also due to the availability of third party seller tools that increase DDD (e.g., https://www.3dsellers.com/blog/top-5-ebay-analytics-and-product-research-tools).

[17] Out of the 260 respondents who reported their store characteristics, 140 are adopters, and 120 are non-adopters. Adopters thus constitute 53.6% of all survey respondents, and 53.8% of respondents with store characteristics.

[18] See Appendix A5.1. for an analysis using alternative definitions of DDD metrics with qualitatively similar results.

Table 1. SH Adoption and Changes in DDD

	Dependent variable:			
	$d\mathbb{I}_{DDD}$	ΔDDD	$d\mathbb{I}_{DDD}$	ΔDDD
	logistic	*OLS*	*logistic*	*OLS*
	(1)	(2)	(3)	(4)
dSH	1.50*** (0.51)	0.85*** (0.25)	1.59*** (0.58)	0.72** (0.29)
$dLearning$			1.29*** (0.49)	0.53* (0.30)
dEd			-0.17 (0.45)	0.14 (0.28)
$dStrongQuantPref$			-0.57 (0.46)	0.04 (0.29)
$dOtherOnlineChannels$			0.24 (0.45)	-0.33 (0.29)
$dBrickNMortar$			-0.23 (0.65)	-0.003 (0.40)
$numFTEs(M)$			0.005 (0.52)	0.13 (0.34)
$numFTEs(L)$			-0.27 (0.79)	0.71 (0.53)
$numLocations(2-3)$			-0.18 (0.51)	0.07 (0.35)
$numLocations(4\ or\ more)$			-0.52 (1.17)	-0.41 (0.81)
$Constant$	-3.30*** (0.46)	1.31*** (0.18)	-3.70*** (0.69)	1.19*** (0.33)
Observations	304	304	260	260
Adjusted R^2		0.03		0.02
Log Likelihood	-87.94		-73.36	
LR χ^2	11.004		22.329	
$Prob > \chi^2$	0.0009***		0.0135**	
Akaike Inf. Crit.	179.88		168.71	
F Statistic		11.37*** (df = 1; 302)		1.63* (df = 10; 249)
Note:	**** p<0.01, ** p<0.05, * p<0.1*			

4. Panel Data and Main Empirical strategy

To study the impact of SH access, we analyze proprietary data from eBay at the seller level, for US-based commercial sellers included in SH's randomization-based ramp-up. Our weekly panel data begins in the first week of March 2016, such that we observe seller activity starting two months prior to the first ramp-up date, and ends in the first week of August, just before SH access was fully ramped-up among eBay's B2C segments. This time frame means that the August 8 ramp-up group remains without access to SH throughout our period of analysis.

Studying commercial sellers on eBay, the target segment of SH's 2016 launch, we include in our sample sellers with sales of at least 10,000 USD in 2015. This threshold roughly corresponds to eBay's internal definition of commercial sellers, though eBay's definition is based on activity in the trailing 12 months, while we use annual sales in the year prior, which provides an exogenous criterion for sample inclusion.[19] We further clean out 19,548 sellers who volunteered to participate in SH beta testing, and thus exhibit SH

[19] Since access to SH may impact performance in 2016.

activity prior to their designated ramp-up date. For these beta testers, access to SH is not based on random assignment, and hence they are not included in our analysis of the randomization-based ramp-up.[20] This process yields panel data of 184,222 B2C sellers' weekly activity on eBay. Our reporting of summary statistics is restricted in compliance with eBay's data policy.

We graph the sales trend for each ramp-up group compared to that of the August 8 ramp-up group, both before and after the former's SH invitation date, in Figure 3, as preliminary visual evidence of an effect of SH access on weekly dollar sales. For each of the ramp-up groups (in each panel of Figure 3), we observe that the average sales trend for sellers in the focal group is highly similar to that of sellers in the final ramp-up group before the group's respective ramp-up date, and that these sales trends diverge after the focal group receives access to SH, with the focal group's sales trend shifting upward.[21]

Formally, we identify the causal impact of SH access by exploiting the experimental setting arising from the gradual *uid_mod*-based launch of SH among US-based B2C sellers described above. We estimate the effect of SH access by comparing sales before and after receiving the invitation to access SH, between sellers in different ramp-up groups. This analysis is performed using the following generalized DiD specification, where sw represents $seller - week$:

$$(2)\ \log(Sales_{sw}) = \alpha_s + \beta_w + \boldsymbol{\delta} \cdot SHaccess_{sw} + \epsilon_{sw}$$

We thus estimate the impact of access to SH at the seller-week level. $Sales_{sw}$ is the sales revenue in USD for seller s in week w plus one dollar, which allows us to include weeks with zero sales in the estimation. We define the binary variable $SHaccess_{sw}$ to equal 0 until the week in which seller s's *uid_mod*-based ramp-up date occurs, and 1 from the following week onwards. Our model includes fixed effects for seller and week, represented by α_s and β_w, to control for unobserved characteristics constant at the seller level (e.g., aptitude at eBay selling, communication skills, etc.), and for e-commerce trends at the week level. The idiosyncratic error term is ϵ_{sw}. Standard errors are clustered at the seller level throughout the paper, accounting for serial correlation in seller performance. We are interested in estimating δ, which is the effect of $SHaccess$ on sales.

Assignment to ramp-up groups based on *uid_mod* is equivalent to randomization-based assignment. Hence, $SHaccess$ is exogenous, and uncorrelated with seller characteristics. While equivalent to random sampling, this assignment process does not take into account the lognormal distribution of commercial seller size, measured in dollar sales (Bar-Gill et al. 2017). Given the heavy-tailed distribution of seller size, stratified

[20] These sellers were eager to use SH, which is likely to imply larger than average returns to SH. Their absence from our panel may therefore lead to a small underestimation of the impacts of SH, as they comprise approximately 10% of the number of sellers in our panel.

[21] Note that for the July 26 group both trends shift upward, yet the post-SH access trend reflects just 2 weeks of data.

SH Access and Sales Trend: Each Ramp Group vs. the Aug. 8 Group, before and after Ramp-Up

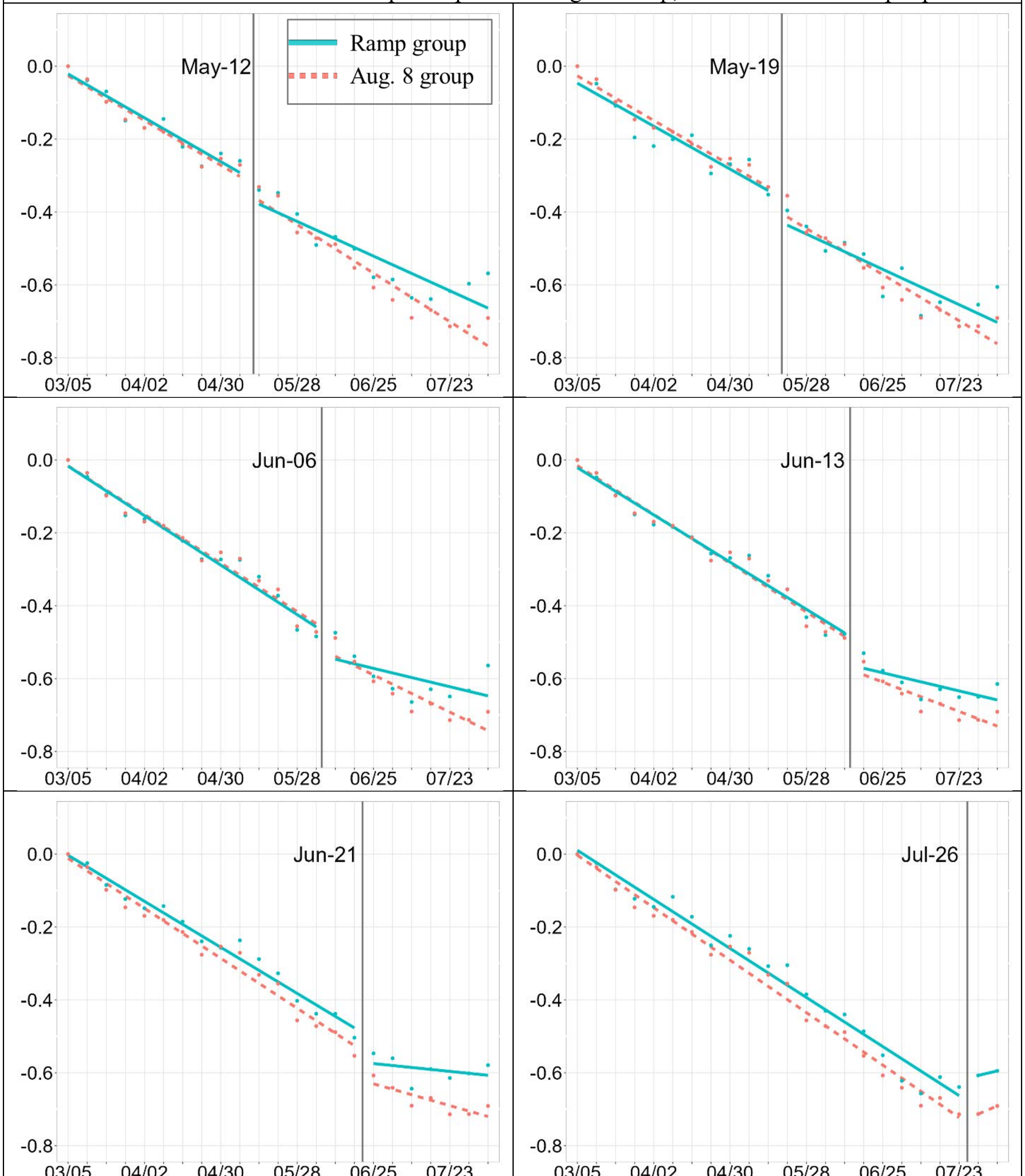

Figure 3. Sales Trends Diverge after each Ramp-Up Date of SH Access.

Each panel compares the linear trend of the log of average weekly dollar sales for one ramp-up group (solid blue) to that of the Aug. 8 group (dashed red), averaged over all sellers in each group, before and after the respective ramp-up date, represented by the vertical line in each panel (the ramp-up date is denoted on its left). Each group's average log of sales is normalized to its level in the first week of March 2016 (in keeping with eBay's data policy).

sampling into ramp-up groups would have provided a better approach, and the lack of stratification may result in some group imbalance. We thus conduct randomization tests, verify that each group's pre ramp-up sales trend parallels that of the August 8 group, and run additional robustness tests (see Section 6.1).

We note that on each ramp-up date, sellers in the appropriate *uid_mod* range were invited to opt-in rather than onboarded to SH. This implies an intent-to-treat (ITT) experimental design, common in many policy settings and product introductions. Therefore, specification (2) estimates the impact of access to SH, rather than the impact of the SH tool. To further estimate the effect of treatment on the treated (TOT), we write specification (2) as an instrumental variables (IV) regression where $SHaccess$ is an instrument for SH adoption, denoted $SHadoption$. The first stage of the IV regression is specified in equation (3a), and the second stage in (3b):

$$\text{(3a)}\ SHadoption_{sw} = \alpha_s + \beta_w + \gamma \cdot SHaccess_{sw} + \epsilon_{sw}$$

$$\text{(3b)}\ \log(Sales_{sw}) = \alpha_s + \beta_w + \boldsymbol{\delta^{IV}} \cdot SHadoption_{sw} + \epsilon_{sw}$$

The TOT IV estimate, $\boldsymbol{\delta}^{IV}$, is the effect of SH adoption on compliers. This estimate may be biased since the exclusion restriction, which, in our setting requires that the invitation to access SH affect outcomes only via adoption of SH, may not necessarily hold.[22] This is because sellers often use third-party tools for optimizing their eBay selling, where these tools may enhance seller performance via listing automation, price optimization, or by providing seller analytics.[23] It is plausible that the SH invitation serves as a reminder or encouragement for sellers to use other tools they may already have had access to and are familiar with, such that some non-compliers may be responding to the invitation by increasing their use of third-party tools (or simply by becoming more data-driven even without additional tools), in violation of the exclusion restriction. Furthermore, the SH invitation may lead sellers to discuss their tools and processes with fellow sellers and facilitate sharing and learning best practices even without adoption.

The TOT IV estimate, which rescales the ITT estimate derived from specification (2) by the share of compliers, will be upward biased when the exclusion restriction isn't satisfied, and will be more sensitive to violations of the exclusion restriction when the odds of non-compliance are large (Angrist et al. 1996). Since 24.88% of sellers adopt SH in our timeframe of analysis, it follows from the above discussion that the TOT IV estimate is likely to be upward biased and therefore serves as an upper bound of the impact of

[22] The other three conditions for an unbiased TOT IV estimate (Theorem 4.4.1 in Angrist and Pischke 2009) hold in our setting: (1) Random assignment to ramp-up groups implies that the IV is independent of the outcome; (2) The first stage exists since access to SH has a non-zero effect on adoption (see Table 2 column (2)); (3) Monotonicity holds since sellers who have yet to receive an invitation to opt-in to SH cannot opt-in.

[23] For example, https://www.inkfrog.com/ is a popular listing tool, https://www.repricer.com/, which also offers seller analytics, is a price optimization tool for e-retailers, and see https://www.3dsellers.com/blog/top-5-ebay-analytics-and-product-research-tools for tools specifically designed to provide analytics capabilities.

SH adoption. The corresponding lower bound of the effect of SH adoption on sales is the ITT estimate of specification (2), as the ITT and TOT estimates equate when the compliance rate is 100%.

In addition to the IV estimation, we derive the effect of SH access for early adopters by running specification (2) for a subsample of SH adopters, who opted-in within one week of their respective ramp-up dates. We focus on a 1-week timeframe since 66.26% of those who adopt SH in our period of analysis do so within 1 week of their invitation date,[24] and because ramp-up dates in May, as well as in June were one week apart, thus precluding an analysis based on a longer adoption window. For this subsample of early adopters, identification of the SH effect is again based on the randomization-based differences in the timing of SH access. The 100% adoption rate for this subsample implies that the SH effect estimated, denoted δ^{EA}, is both the ITT effect and the effect of TOT. Based on the unobserved characteristics of early adopters, such as higher education attainment and tech-savviness (Rogers 2003, Waarts et al. 2002), the SH effect for this subsample may be either lower or higher than for the average B2C seller, as follows. On the one hand, having advanced education and an affinity for new technology may imply a higher aptitude for analytics and DDD such that benefits from SH would be higher; on the other hand, it may imply higher baseline levels of analytics and DDD, such that the impact of SH would be smaller (under decreasing marginal productivity of DDD). We thus regard δ^{EA} as providing robustness to our ITT and TOT IV estimates and expect its magnitude to fall between the lower and upper bounds they set, that is, δ^{EA} will be in the $[\delta, \delta^{IV}]$ range.

Finally, we estimate the dynamic impact of $SHaccess$ using a relative time model specification (as in Chan and Ghose 2014, Greenwood and Wattal 2017):

$$\text{(4)}\quad \log(Sales_{sw}) = \alpha_s + \beta_w + \sum_t \delta_t \cdot RelWeek_{sw}(t) + \epsilon_{sw}$$

As in (2) and (3), the model includes fixed effects for seller and week, represented by α_s and β_w. Studying the impact of chronological distance from the ramp-up week on $log(Sales)$, we let $t \in \{-8, -7, \dots, 7, 8\}$ denote this chronological distance in weeks, and let $RelWeek_{sw}(t)$ indicate whether week w is t weeks away from seller *s*'s ramp-up date. Note that for $t \in \{-8, +8\}$ $RelWeek_{sw}(t)$ indicates 8 *or more* weeks prior or post ramp-up, respectively. We are interested in $\boldsymbol{\delta_t}$, the estimate of the dynamic impact of access to SH. This approach allows us to verify the parallel trends assumption of our base DiD specification (2) using δ_t estimates for $t \leq -1$, and additionally provides estimates of the SH effect at different points in time following the invitation date.

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[24] These are 43.81% of all adopters (including those who adopt SH after the first week of August 2016).

5. Results

5.1. Overall DDD Impact on Sales

We estimate the average impact of SH on weekly sales using the above specifications and report the results in the following Table 2. Column (1) provides the ITT estimate, measuring the impact of access to SH on weekly sales based on specification (2), column (2) provides the estimation results for the first stage of the TOT IV regression in specification (3a), and column (3) provides the results of the second stage, the effect of TOT. Finally, column (4) reports the impact of SH on early adopters, estimated by running specification (2) on a subsample of sellers who adopt SH within the first week from their ramp-up date. Note that 24.88% of sellers in our panel opt-in to SH in our period of analysis, where 66.26% of these adopters adopt SH within a week of receiving the opt-in invitation.

We find that access to SH leads to a 3.6% increase in weekly sales on average.[25] The first stage of our TOT IV regression demonstrates that the association between the SH invitation and adoption of SH is 0.295 controlling for seller and week fixed effects, which is in line with the observed adoption rates. The second stage estimates for the impact of SH adoption is a 12.5% increase in weekly sales, on average, which we regard as an upper bound of the SH impact, as per the discussion in Section 4.

The SH effect on early adopters is estimated to be a 3.7% increase in weekly sales, on average. The latter is indeed within the upper and lower bounds set by the ITT and TOT estimates, as expected, and is closer to the lower bound. This is in line with our conjecture that the unobserved characteristics of early adopters may correlate with high baseline levels of DDD pre-SH, leading to lower benefits from SH adoption.

Our results thus provide causal evidence of a DDD impact on the performance of small businesses, aligning well with previous estimates based on observational data and quasi-experiments.

Table 2. The Impact of SH Access on Sales - ITT and TOT Estimates

	Dependent variable:			
	ITT	TOT - IV		Early Adopters
	$\log(Sales)$	$SHadoption$	$\log(Sales)$	$\log(Sales)$
	(1)	(2)	(3)	(4)
$SHaccess$	0.035^{***} (0.005)	0.295^{***} (0.001)		0.036^{***} (0.011)
$SHadoption$(fitted)			0.118^{***} (0.019)	
Observations	4,237,106	4,237,106	4,237,106	864,685
Adjusted R^2	0.640	0.480	0.640	0.617
Note:	Seller and week fixed effects included. Cluster robust standard errors shown in parentheses (Clustered on seller). **** p<0.01, ** p<0.05, * p<0.1*			

[25] The effects are calculated based on the exponentiated coefficients, since the dependent variable is in logarithmic scale. This is the case for all results reported in Sections 5.1-5.3.

The SH impact is further evident in the estimation results of our relative time model, reported in Appendix A4 (Table A4.1. column (1)) and depicted in Figure 4 below.

Our estimates point to a positive and increasing effect of SH access on sales revenue, with a 2.5-3.6% increase in weekly sales in the first three weeks following the opt-in invitation, increasing to 4.4-5% in weeks 4-5, and to 6.1-7.7% from week 6 onwards.[26] Moreover, the coefficients of the impact of SH access in the weeks preceding ramp-up are not statistically significant, implying that the sales trends of the different ramp-up groups run parallel pre-ramp-up, such that our use of the DiD framework is indeed valid. Additional robustness tests are reported in Section 6.1.

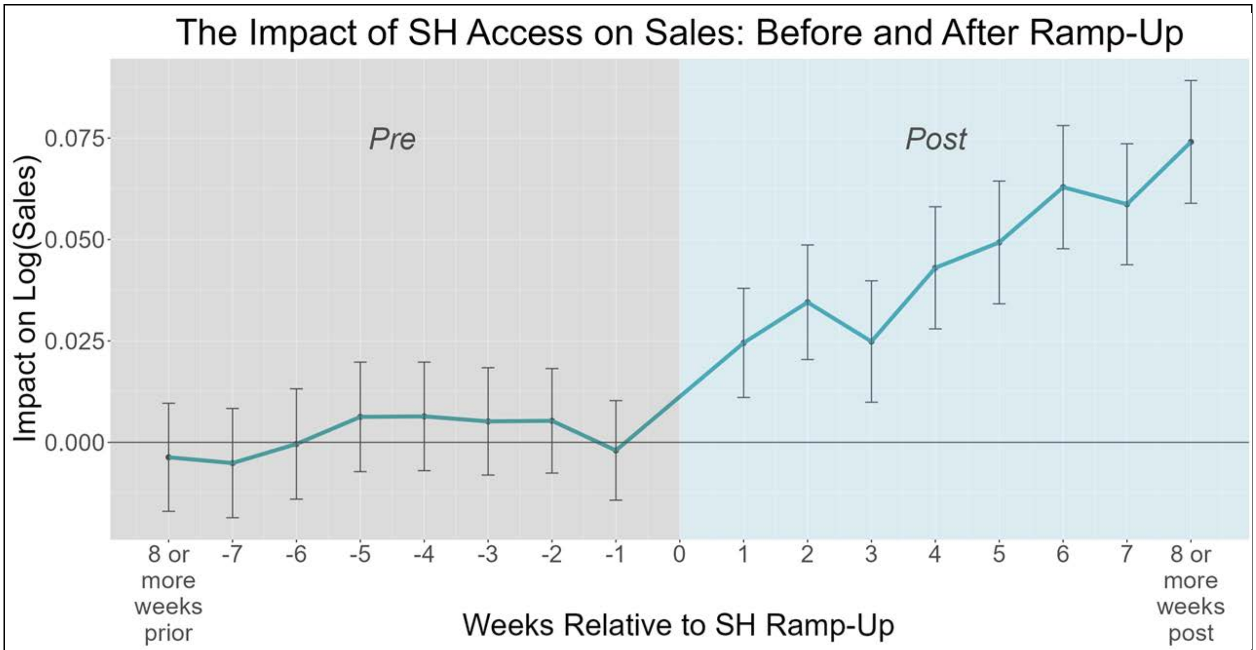

Figure 4. The Impact of SH Access in each Week Pre and Post Ramp-Up.
The graph depicts SH access effects for each relative week estimated using the relative time model.

5.2. Drivers of the DDD Impact on Sales

We decompose the SH access effect on sales, by exploring the impacts of increased DDD on seller activity. We specifically study the SH impact on quantities sold, average price of sold items, feedback scores, and new listing activity. This analysis will allow us to determine whether the focal effect on sales is driven by increases in quantity or in price, and to further study the SH impact on an indirect revenue driver— service quality. A SH effect on listing creation will provide additional evidence of an impact on quantity sold, as

[26] Note that the week in which the SH access invitation is sent out is week 0, and inivitations were sent on Mondays (for the June 6th and 13th groups), Tuesdays (for the June 21st and July 26th groups), and on Thursdays (for the May 12th and 19th groups). Since weekly sales are the sum of sales accrued by the end of each week, a sales effect in week 1 represents an increase in sales in the second week of SH access, rather than an instantaneous effect.

these are highly correlated (Appendix A3). [27]

We run our main specifications (2) and (3), estimating the ITT and TOT effects for our panel of B2C sellers, and the effect of SH for early adopters, for the following dependent variables: (A) $Quantity_{sw}$ is the number of items sold by seller s in week w plus one (to allow the inclusion of weeks with zero sales in the estimation); (B) $Price_{sw}$ is the average price of items sold by seller s in week w, computed only for weeks with a positive number of items sold; (C) $Feedback_{sw}$ is the feedback score for seller s in week w, where the score is updated with each rating the seller receives from a buyer, increasing (decreasing) by 1 point for a positive (negative) rating, or getting 0 points for a neutral rating; (D) $NewListings_{sw}$ is the number of new listings added by seller s in week w plus one (to allow the inclusion of weeks with a value of zero in the estimation).[28] Our results are reported in Panels A-D of Table 3. Note that the first stage of the TOT IV regression is unchanged from Table 2 column (2), and thus not reported again in Table 3.[29]

Our results suggest that increases in DDD lead to increases in quantity sold, without increasing the average price of sold items. DDD further increases the quality of service as represented by feedback scores and drives sellers to add more new listings, likely in response to the increases in demand.[30] Specifically, we find that SH access leads to a 1.3%-4.5% increase in the number of items sold, on average, based on our ITT and TOT estimates (Panel A, (1) and (2)), with an effect of 1.2% on the subsample of early adopters (Panel A, (3)).[31] The effect of increased DDD on price is not statistically significant (Panel B), though we do observe a marginally significant ($p < 0.1$) effect for early adopters, whose average price of sold items increases by 0.8%. Sellers' feedback scores increase by 0.2%-0.6%, on average, as a result of SH access (Panel C, (1) and (2)), and by 0.4% for early adopters (Panel C, (3)). Finally, SH access leads to a 0.9%-3.1% increase in the number of new listings, on average (Panel D, (1) and (2)), with no significant effect found for early adopters.

The main effect of enhanced DDD on sales is thus driven by increases in quantity, rather than in price of items sold. Furthermore, this increase in transactions is driven, at least in part, by improved service quality as represented by the increase in feedback scores, and enabled by an increased supply of items as evident from the increase in the number of new listings. Overall, increases in DDD offer benefits for *both* sellers

[27] Feedback scores and quantity sold on eBay are also highly correlated, yet their partial correlation controlling for seller and week fixed effects in not statistically significant in our panel. The effect of SH on feedback can thus be estimated as separate and distinct from the effect on quantity sold (see Appendix A3).

[28] The count of new listings may include both new listings of items previously offered by the seller, as well as listings of newly available products. Our data does not allow us to cleanly distinguish between these two types of new listings.

[29] The dynamic effect of SH access on these dependent variables is estimated using the relative time model (specification (4)), and the results are reported and discussed in Appendix A4.

[30] This is further evident from the delayed effect of SH access on *NewListings* (see Appendix A4).

[31] Considering the coefficients' standard errors, the estimated effect for early adopters is very close to the lower bound provided by the ITT.

and buyers, as more items are offered and transacted without increases in average price, and service quality is improved. We note that the effect of increased DDD on quantity sold, as well as the null effect on price are consistent with the effects of adoption of an analytics dashboard reported for large e-retailers (Berman and Israeli 2022).

Table 3. The Impact of SH Access on Quantity, Price, Feedback, and Number of New Listings

	ITT	TOT IV	Early Adopters
	(1)	(2)	(3)
Panel A. Quantity		*Dependent variable:* $\log(Quantity)$	
$SHaccess$	0.013^{***} (0.002)		0.012^{**} (0.005)
$SHadoption$(fitted)		0.044^{***} (0.008)	
Observations	4,237,106	4,237,106	864,685
Adjusted R^2	0.818	0.818	0.828
Panel B. Price		*Dependent variable:* $\log(Price)$	
$SHaccess$	0.002 (0.002)		0.008^{*} (0.004)
$SHadoption$(fitted)		0.006 (0.006)	
Observations	3,193,034	3,193,034	737,921
Adjusted R^2	0.655	0.655	0.674
Panel C. Feedback		*Dependent variable:* $\log(Feedback)$	
$SHaccess$	0.002^{***} (0.001)		0.004^{***} (0.001)
$SHadoption$(fitted)		0.006^{***} (0.002)	
Observations	4,235,184	4,235,184	864,486
Adjusted R^2	0.995	0.995	0.996
Panel D. New Listings		*Dependent variable:* $\log(NewListings)$	
$SHaccess$	0.009^{***} (0.003)		-0.004 (0.007)
$SHadoption$(fitted)		0.031^{***} (0.009)	
Observations	4,237,106	4,237,106	864,685
Adjusted R^2	0.616	0.616	0.589

Note: Seller and week fixed effects included.
Cluster robust standard errors shown in parentheses (Clustered on seller).
**** p<0.01, ** p<0.05, * p<0.1*

These results are in line with classic arguments about the effect of information on firms' ability to differentiate, such that information and IT can create a competitive advantage (Porter and Millar 1985). As examples of how improved information via SH can help sellers differentiate, we consider information from SH's traffic report, as well as from the feedback and seller level reports. Improved tracking of listings' impressions in the traffic report can help sellers identify changes in demand ahead of their competitors, adjust their inventory, and create new listings faster. This can explain the positive SH impact on quantity sold and new listing creation. Considering the effect on feedback scores— closely tracking seller level and feedback can help sellers maintain a high standing, which affects their listings' ranking in search results.[32] Hence, both use cases demonstrate how improved information through SH creates a competitive advantage, allowing sellers with access to SH to sell larger quantities than their counterparts who had yet to receive access, without lowering their average prices.

We continue to explore the hypothesis that SH access creates a competitive advantage, by examining its impacts for sellers in homogeneous vs. differentiated product categories. If, indeed, improved information and SH-enhanced DDD help sellers differentiate and build their competitive advantage, then we expect to see larger benefits from SH for sellers in product categories with lower differentiation, namely, in homogeneous categories (as the marginal benefit of enhanced differentiation would be larger when the baseline level of differentiation is lower). We hereby test this hypothesis.

Since our variables are at the seller-week rather than product or listing level, we create an indicator of whether sellers' activity in each week is predominantly in a homogeneous or nonhomogenous product category. To this end, we define $MainCategory_{sw}$ as the product category in which seller s had the highest revenue in week w, and consider homogeneity at the product category level.[33] We define homogeneous and differentiated product categories based on the percent of listings in each category that have an auto-tagged ePID (eBay Product ID), an automatically populated field added to listings of well-identified products that are mostly mass-produced, such as books, cellphones, and automobile parts, while typically remaining unpopulated for products that cannot be defined by a model number or publisher ID (e.g., ISBN) or have hard-to-define attributes, such as antiques and fashion items. The availability of auto-tagged ePIDs in a product category is used as a proxy for the level of product differentiation within the category. That is, categories with a large share of listings with auto-tagged ePIDs are more homogenous than categories where the share of auto-tagged ePIDs is small (this approach is similar to the one in Brynjolfsson et al. 2019).[34] We consider the top four main categories in terms of availability of auto-tagged ePIDs as homogeneous categories, and the bottom four as differentiated. Hence, homogeneous main categories are: Media, Parts & Accessories, Electronics, and Business & Industrial, while Home & Garden, Lifestyle, Collectibles and Fashion are considered differentiated categories.

We define the indicator $Homog_{sw}$ to equal 1 when $MainCategory_{sw}$ is one of the above-mentioned homogeneous categories, and 0 otherwise, and note that 17.21% of our panel consists of sales in

[32] Along with other factors, see https://www.sellbrite.com/blog/ebay-sales-conversion-rate/.
[33] For robustness, we repeat this analysis with a quantity-based definition of $MainCategory_{sw}$, see Appendix A5.7.
[34] The percent of listings with auto-tagged ePIDs in each main category is computed for all listings posted on eBay between January 1st and 7th, 2023 and reported in Appendix A5.7.1. The most homogeneous category, by share of listings with auto-tagged ePIDs is Media at 58.6%, and the least homogeneous is Fashion at 5.7%.

homogeneous product categories (i.e., $Homog_{sw} = 1$ for 17.21% of our seller-week pairs).[35]

We estimate the differential effect of SH access in homogeneous vs. nonhomogeneous product categories using the following specification:

$$(5)\ \log(DV_{sw}) = \alpha_s + \beta_w + \delta_1 \cdot SHaccess_{sw} + \delta_2 \cdot Homog_{sw} + \boldsymbol{\delta_3} \cdot SHaccess_{sw} \times Homog_{sw} + \epsilon_{sw}$$

This is our main ITT specification, with an added control for selling mostly in a homogeneous product category, $Homog_{sw}$, as well as its interaction with SH access, such that δ_3 represents the moderating effect of category homogeneity on the impact of SH access. DV_{sw} is one of $\{Sales_{sw}, Qunatity_{sw}, Price_{sw}, Feedback_{sw}, NewListings_{sw}\}$, and all other variables are as defined in specification (2).[36]

Table 4. The Effect of SH Access, by Homogeneity of Product Categories

	Dependent variable:				
	$\log(Sales)$	$\log(Quantity)$	$\log(Price)$	$\log(Feedback)$	$\log(NewListings)$
	(1)	(2)	(3)	(4)	(5)
$SHaccess$	0.010*	0.005**	0.0004	-0.001*	0.007**
	(0.006)	(0.002)	(0.002)	(0.001)	(0.003)
$Homog$	2.233***	0.588***	-0.040***	-0.002***	0.227***
	(0.011)	(0.004)	(0.003)	(0.001)	(0.003)
$SHaccess \times Homog$	0.130***	0.040***	0.008**	0.016***	0.013***
	(0.007)	(0.003)	(0.003)	(0.001)	(0.005)
Observations	4,237,106	4,237,106	3,193,034	4,235,184	4,237,106
Adjusted R^2	0.671	0.825	0.655	0.995	0.617
Note:	Seller and week fixed effects included.				
	Cluster robust standard errors shown in parentheses (Clustered on seller).				
	**** p<0.01, ** p<0.05, * p<0.1*				

The results reported in Table 4 suggest that the impact of enhanced DDD is stronger in homogeneous product categories, as hypothesized. Specifically, the sales increase due to SH access is 13.9% higher for sellers in homogeneous categories and quantity sold is 4.1% higher, as per the estimated interaction coefficients in models (1) and (2). Sellers in homogeneous categories on eBay have overall higher weekly sales, larger quantities sold, and post more new listings each week, while selling at lower prices and having lower feedback scores, as evident from the estimated δ_2 representing the association between category homogeneity and our dependent variables. This is in line with the stronger competition expected in homogeneous markets. Yet access to SH mitigates price pressures and helps sellers of homogeneous products improve their service quality, as average prices increase by 0.8% and feedback scores by 1.6%

[35] Our identification of homogeneity at the seller-week level is imperfect by definition. We therefore discuss this limitation and run a series of robustness tests in Appendix A5.7.2., providing support to the findings reported here.
[36] We focus on the ITT estimate. As in prior analyses, the TOT estimate is equal to the ITT estimate scaled up by the share of adopters.

over sellers in nonhomogeneous categories, based on the interaction coefficients in models (3) and (4). The impact on feedback scores for sellers in homogeneous markets is aligned with previous accounts of differentiation via service quality and trust (Brynjolfsson and Smith 2000, Pan et al. 2002), and the positive impact on price suggests that these sellers indeed gain a competitive advantage.[37] Finally, sellers in homogeneous categories create 1.3% more new listings a week than sellers in differentiated categories due to SH access (model (5)).

Overall, access to better analytics and enhanced DDD provide larger benefits in markets with lower differentiation, allowing sellers in homogeneous categories to differentiate themselves and increase their price premiums.

5.3. The Moderating Role of Performance Monitoring

Previous work has highlighted the importance of managerial practices that are complementary to investments in IT and analytics, in driving benefits from these tools and capabilities (e.g., Bharadwaj et al. 2007, Bloom et al. 2014, Devaraj and Kohli 2003). Furthermore, the examples in Section 5.2, demonstrating how sellers may use improved information on traffic and service quality to gain a competitive advantage, highlight the importance of actively monitoring reports on SH to increase revenue. We therefore investigate the contribution of the practice of performance monitoring to the impact of SH.

Visits to SH's Performance tab represent the practice of monitoring business performance, as it includes sales, traffic, feedback, and seller level reports. Utilization of the Performance tab is not high, with early adopters averaging 0.64 Performance visits a week, since highlights from the Performance tab are featured in SH's landing page, the Overview tab, which has 24.89 weekly visits by the average early adopter. Yet, Performance tab visits provide a cleaner measure of performance monitoring than visits to the Overview tab, as the latter presents information on all selling-related tasks (e.g., orders requiring attention and messaging with buyers) alongside performance graphs and reports from the Performance tab. We thus use visits to the Performance tab as a measure of monitoring extent.[38]

We study the moderating role of performance monitoring on the effect of SH access on sales, by adding the interaction of $SHaccess_{sw}$ and $PerformanceVisits_{sw}$ to specification (2), where $PerformanceVisits_{sw}$ is defined as seller s's weekly number of visits to the Performance tab, and all other variable and parameter definitions are as in specification (2). We note that $PerformanceVisits_{sw}$ can take positive values only

[37] Differentiation has been proposed as a leading explanation for price dispersion in homogeneous markets. Differentiation strategies studied include: service differentiation (Pan et al. 2002), branding and trust (Brynjolfsson and Smith 2000), and offering different versions of a searched product (Clemons et al. 2002).

[38] Our survey data includes another metric for monitoring extent: sellers' reported number of KPIs tracked. Yet, as a survey metric it is only available for the 304 survey respondents, and thus used in Section 3.3 as a component of our DDD metrics. Here we focus on performance monitoring as represented in our panel data.

when $SHaccess_{sw}$ equals 1 and seller s has opted-in to SH. This implies that the interaction term in the following specification (6) is equivalent to $PerformanceVisits_{sw}$ alone, yet we write the interaction to emphasize the view of performance monitoring as a moderator. We focus on early adopters because, for them, SH access equals adoption, such that their number of Performance tab visits is indicative of monitoring or lack thereof, whereas for later adopters, zero Performance visits are observed both prior to SH opt in, as well as in post-opt in weeks with no active monitoring. We thus estimate the following model for early adopters, reporting the results in column (1) of Table 5 below.

$$(6)\ \log(Sales_{sw}) = \alpha_s + \beta_w + \boldsymbol{\delta_1} \cdot SHaccess_{sw} + \boldsymbol{\delta_2} \cdot SHaccess_{sw} \times PerformanceVisits_{sw} + \epsilon_{sw}$$

Our results point to the importance of managerial performance monitoring in generating value from SH. The moderation analysis breaks down the effect of SH access to a standalone impact of access to SH of a 2.5% increase in weekly sales, and an additional increase of 1.4% with each weekly visit to the Performance tab. This suggests that over a third of the SH impact is driven by active performance monitoring.

We test the robustness of this result by extending specification (6) to study the moderating role of both the Performance and Growth tabs. The Growth tab provides sellers with data-based machine recommendations for listing optimization aimed at increasing conversion rates, as well as competitive guidance based on similar listings, and was in Beta mode in the period of our analysis. Together, the Performance and Growth tabs embody the new functionalities introduced in SH, while other tabs, namely, Orders, Listings, and Marketing, provide access to previously available functionalities.[39] We define $GrowthVisits_{sw}$ as seller s's weekly number of visits to the Growth tab, and note that, similarly to $PerformanceVisits_{sw}$, $GrowthVisits_{sw}$ can only take positive values after a seller has opted in to SH. For our sample of early adopters, the average weekly number of Growth visits is 0.45, and the correlation between Performance and Growth visits is 0.155.

Estimation results reported in column (2) of Table 5 show a baseline SH effect of 2.3% with additional sales increases of 1.3% and 0.6% with each weekly visit to the Performance and Growth tabs (respectively). These results further attest to the valuable role of managers' performance monitoring, and to the robustness of the estimation results with $PerformanceVisits$ alone.[40]

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[39] The Overview tab contains both highlights of previous and new functionalities, yet the strong correlation between visits to the Overview tab (the landing page of SH) and SH access ($\rho = 0.396$) precludes valid estimation of the moderating role of Overview visits.

[40] A moderation model with $GrowthVisits$ alone yields an estimated SH effect of 3.1% with an additional 0.8% sales increase with each weekly Growth visit. Since the Growth tab was in Beta mode in 2016, we view this as a lower bound for its impact, and focus on the impact of performance monitoring as a key component of DDD, which we can more precisely estimate.

Table 5. The Moderating Role of Performance Monitoring on Early Adopters.

	Dependent variable:	
	log($Sales$)	
	(1)	(2)
$SHaccess$	0.025** (0.011)	0.023** (0.011)
$SHaccess \times PerformanceVisits$	0.014*** (0.002)	0.013*** (0.002)
$SHaccess \times GrowthVisits$		0.006*** (0.001)
Observations	864,685	864,685
Adjusted R^2	0.617	0.617

Note: Seller and week fixed effects included.
Cluster robust standard errors shown in parentheses (Clustered on seller).
**** p<0.01, ** p<0.05, * p<0.1*

6. Robustness Tests

6.1. Validity of Empirical Strategy and Results

SH's rollout based on sellers uid_mod implies an assignment to ramp-groups which is equivalent to random assignment. Yet, this uniform randomization process does not take into account the heavy tailed distribution of firm sizes on eBay (Bar-Gill et al. 2017), which calls for a stratified sampling approach. To alleviate this concern, we conduct a series of robustness tests to verify that ramp groups were sufficiently balanced, with parallel pre-ramp up sales trends, and that our results are not driven by one of the groups.

First, we visualize the distribution of annual sales in 2015, the year prior to the SH launch, for each ramp-up group in Appendix Figure A5.2.1. The figure does not point to a significant difference in means between the groups, yet does point to some differences in the right tail of large sellers included in each group, as are expected due to the uniform random sampling from a heavy tailed distribution of seller sizes (in sales). We thus conduct a Kruskal Wallis rank sum test to examine differences between ramp-up groups in their median of annual sales in 2015, and do not reject the null hypothesis of equal medians ($\chi^2 = 10.732,\ p = 0.10$).

We proceed to directly test the parallel trends assumption underlying the generalized DiD specification (2). We employ the following model to directly test for differences in trends between each ramp-up group and the Aug. 8 group in the pre-SH period (as in Gallino and Moreno 2014):

$$(7)\ \log(Sales_{sw}) = \alpha_s + \beta_1 \cdot Trend_w + \boldsymbol{\beta_2} RampGroup_s \times Trend + \epsilon_{sw}$$

where $RampGroup_s$ represents seller s's ramp-up group, and $Trend_w$ is week w's index running from 1 for the week of March 1st to 11 for the week of May 12th, as we focus on the pre-SH ramp-up period. Thus, β_1 represents the common sales trend for both groups, fixed effects for seller are represented by α_s, controlling for seller-level differences, and the idiosyncratic error term is ϵ_{sw}, as before. We estimate the model for each ramp-up group compared to the Aug. 8 group, testing for trend differences in sales in the pre-SH period. Our coefficient of interest is β_2, capturing differences in the sales trend between the focal and final ramp-up groups. If the parallel trends assumption indeed holds, the confidence interval for our estimate of β_2 will include 0. Results, reported in Appendix Table A5.3.1, validate the parallel trends assumption. Indeed, β_2, the coefficient of the interaction $RampGroup \times Trend$ is not significantly different from 0 in all six estimations, comparing each ramp-up group, in turn, to the Aug. 8 group. This implies that the pre-SH sales trend for each group parallels that of the August 8 group.

We proceed to verify that our main results are not driven by one of the ramp-up groups, due to the non-stratified group assignment, by re-estimating our main specifications (2) and (4), now omitting one ramp-up group at a time. Results for six such iterations are reported in Appendix Tables A5.4.1 and A5.4.2, respectively. This series of regressions attests to the robustness of our main results, demonstrating that they remain unchanged as we omit each ramp-up group from the estimation. Finally, we estimate the SH access effect with recently proposed heterogeneity-robust DiD estimators for models with staggered treatment timing (Appendix A5.5), further validating our results.

6.2. The SH Impact by Seller Size

Since earlier research has found DDD effects for large publicly traded firms, we proceed to test whether the average SH impact we find is driven by a particular segment.

Sellers at eBay are internally classified as *commercial sellers* if they complete at least 100 transactions, totaling at least $10,000 in sales revenue in the trailing 12 months. These B2C sellers are internally divided into three segments based on their trailing 12-months sales revenue. *Entrepreneurs* are the lowest-volume sellers classified as B2C with sales between $10,000 and $120,000, *Merchants* are the middle segment with sales between $120,000 and $1 million, and *Large Merchants* are the top segment with sales over $1 million. Our sample consists of 165,273 Entrepreneurs (89.7% of the sample), 17,814 Merchants (9.7%) and 1,135 Large Merchants (0.6%). The relative sizes of the segments are consistent with the heavy tailed distribution of firm sizes on the eBay platform (Bar-Gill et al. 2017).

We perform our main analysis, running eq. (2)-(4), in each segment separately, to explore heterogeneity by seller segment ($Sgmnt$) in the impact of $SHaccess$. Estimation results are reported in Appendix Table A5.6.1. We find that access to SH leads to a 3% increase in sales for Entrepreneurs, and a 4% increase for Merchants. The effect on sales in the Large Merchants segment in not statistically significant ($p = 0.501$). A possible explanation for this null effect may be that some of these larger sellers were already using non-eBay analytics tools prior to the introduction of SH, such that SH is substituting for another tool rather than adding new capabilities, thereby mitigating the treatment effect.[41] Note that this null effect does not

[41] We cannot test this potential substitution, as we do not have data on sellers' use of third-party analytics tools.

contradict prior findings on the impacts of analytics for large firms, as the Large Merchants studied here all have annual sales revenues below 100 million dollars on eBay, whereas large publicly traded firms typically have annual sales surpassing 1 billion dollars.[42] Furthermore, we are limited to the study of the SH impact on eBay sales, while large e-retailers are likely to operate via additional online and offline channels.

The analysis of the SH impact by segment suggests that the average effect found in our study is not driven by the largest sellers in our sample. This result highlights the fact that while previous research has identified the effect of analytics on large enterprises and firms, we find a causal effect of an analytics dashboard on small businesses.

7. Concluding Remarks

We provide causal evidence for the effect of analytics and DDD on SMEs, by studying the randomized introduction of eBay's SH tool. We find that access to a DDD tool increases small e-retailers' weekly sales by 3.6% on average, increasing the quantity of items transacted, while prices do not change. The increase in transactions is enabled by DDD-driven increases in service quality and supply. Our results are in line with an information and IT-driven creation of competitive advantage, likely based on differentiation via service quality and improved demand tracking (Porter and Millar 1985).

Measuring the positive impacts of analytics and DDD on SMEs is particularly important considering their uneven adoption patterns (Brynjolfsson and McElheran 2016, Llave 2017), and our findings may guide SME managers, digital platforms, and small business authorities' policy. For managers of SMEs, our estimates may guide investments in analytics tools and capabilities, as well as highlight the necessary managerial practices for successful DDD.

For platform owners, our results suggest that platforms matching supply and demand (e.g., e-commerce and freelance work platforms) could support SMEs by embedding analytics tools. These would increase the revenue of small businesses on the platform, and thus increase platform revenues from both fees and new entrants, as it becomes more attractive to SMEs. Broadly speaking, we demonstrate the importance of platform policies that reduce fixed costs of technology adoption for small businesses, whose small scale often leads to underinvestment in technology. We thus relate to another recent example of a cost-reducing platform policy that aided SMEs—eBay's Global Shipping Program, which reduced exporting costs, leading to increased SME exports on the platform by facilitating entry of new exporters (Hui 2019).

Finally, our results imply that the benefits of analytics tools for small businesses are comparable to the benefits of governmental SME aid programs (Appendix A6). Yet, the costs of government programs tend

[42] See https://www.statista.com/statistics/195992/usa-retail-sales-of-the-top-retailers/

to be high, such that aid is awarded to a select subset of applicants.[43] Policy makers could therefore consider analytics tools as a cost-effective means of support that small business agencies may offer to a larger number of firms (e.g., via pooled licensing).[44] Yet, providing analytics tools alone may not be sufficient—accompanying training can ensure that small business managers are equipped to actively monitor their business' performance and fully realize the benefits of these tools.

References

Aker JC (2010) Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *Am. Econ. J. Appl. Econ.* 2(3):46–59.

Angle P, Forman C (2018) Does IT level the playing field for small establishments? Evidence from manufacturing. *SSRN Electron. J.*

Angrist JD, Imbens GW, Rubin DB (1996) Identification of Causal Effects Using Instrumental Variables. *J. Am. Stat. Assoc.* 91(434):444–455.

Angrist JD, Pischke JS (2009) *Mostly harmless econometrics : an empiricist's companion* (Princeton University Press).

Angrist JD, Pischke JS (2010) The Credibility Revolution in Empirical Economics: How Better Research Design Is Taking the Con out of Econometrics. *J. Econ. Perspect.* 24(2):3–30.

Bakos Y (1998) The emerging role of electronic marketplaces on the Internet. *Commun. ACM* 41(8):35–42.

Bar-Gill S, Brynjolfsson E, Hak N (2017) Firm Size Distribution Goes Online: The Evolution of eBay Firms' Sales Distribution. *Work. Pap.*

Barua A, Kriebel CH, Mukhopadhyay T (1995) Information Technologies and Business Value: An Analytic and Empirical Investigation. *Inf. Syst. Res.* 6(1):3–23.

Berman R, Israeli A (2022) The Value of Descriptive Analytics: Evidence from Online Retailers. *Mark. Sci.*

Bharadwaj S, Bharadwaj A, Bendoly E (2007) The Performance Effects of Complementarities Between Information Systems, Marketing, Manufacturing, and Supply Chain Processes. *Inf. Syst. Res.* 18(4):437–453.

[43] For instance, the US Small Business Administration (SBA) spent $201.15 million on grants in 687 transactions with SMEs in 2019 (pre-Covid19), i.e., approximately $292,795 for an average transaction, see https://www.usaspending.gov/agency/small-business-administration?fy=2019

[44] Note that analytics dashboards for SMEs can be licensed for less than $4000 a year: https://loyverse.com/blog/best-analytic-dashboards-for-small-businesses

Bloom N, Brynjolfsson E, Jarmin R, Patnaik M, Saporta-Eksten I, Van Reenen J (2014) IT and Management in America. *Cent. Econ. Perform.* (Discussion paper No. 1258).

Bradlow ET, Gangwar M, Kopalle P, Voleti S (2017) The Role of Big Data and Predictive Analytics in Retailing. *J. Retail.* 93(1):79–95.

Brown JR, Goolsbee A (2002) Does the internet make markets more competitive? Evidence from the life insurance industry. *J. Polit. Econ.* 110(3):481–507.

Brynjolfsson E (1993) The productivity paradox of information technology. *Commun. ACM* 36(12):66–77.

Brynjolfsson E, Hitt L (1996) Paradox lost? Firm-level evidence of high returns to information systems spending. *Manage. Sci.* 42(4):541–558.

Brynjolfsson E, Hitt LM, Kim HH (2011) Strength in numbers: How does data-driven decision-making affect firm performance? *ICIS 2011 Proc.*

Brynjolfsson E, Jin W, McElheran K (2021) The power of prediction: predictive analytics, workplace complements, and business performance. *Bus. Econ.* 56(4):217–239.

Brynjolfsson E, McElheran K (2016) The rapid adoption of data-driven decision-making. *Am. Econ. Rev.* 106(5):133–139.

Brynjolfsson E, McElheran KS (2019) *Data in action: Data-driven decision making and predictive analytics in US manufacturing*

Brynjolfsson E, Smith MD (2000) Frictionless commerce? A comparison of Internet and conventional retailers. *Manage. Sci.* 46(4):563–585.

Bughin J (2016) Ten big lessons learned from Big Data analytics. *Appl. Mark. Anal.*

Cao M, Chychyla R, Stewart T (2015) Big Data Analytics in Financial Statement Audits. *Account. Horizons* 29(2):423–429.

Cardona M, Kretschmer T, Strobel T (2013) ICT and productivity: Conclusions from the empirical literature. *Inf. Econ. Policy* 25(3):109–125.

Chan J, Ghose A (2014) Internet's Dirty Secret. *MIS Q.* 38(4):955–976.

Clemons EK, Hann IH, Hitt LM (2002) Price Dispersion and Differentiation in Online Travel: An Empirical Investigation. *Manage. Sci.* 48(4):534–549.

Davenport T, Harris J (2007) *Competing on Analytics: The New Science of Winning*

Dedrick J, Gurbaxani V, Kraemer K (2003) Information technology and economic performance: A critical review of the empirical evidence. *ACM Comput. Surv.* 35:1–28.

Devaraj S, Kohli R (2003) Performance impacts of information technology: Is actual usage the missing link? *Manage. Sci.* 49(3):273–289.

Gallino S, Moreno A (2014) Integration of Online and Offline Channels in Retail: The Impact of Sharing Reliable Inventory Availability Information. *Manage. Sci.* 60(6):1434–1451.

Germann F, Lilien GL, Fiedler L, Kraus M (2014) Do Retailers Benefit from Deploying Customer Analytics? *J. Retail.* 90(4):587–593.

Germann F, Lilien GL, Rangaswamy A (2013) Performance implications of deploying marketing analytics. *Int. J. Res. Mark.* 30(2):114–128.

Greenwood BN, Wattal S (2017) Show Me the Way to Go Home: An Empirical Investigation of Ride-Sharing and Alcohol Related Motor Vehicle Fatalities. *MIS Q.* 41:163–187.

Hendricks KB, Singhal VR, Stratman JK (2007) The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations. *J. Oper. Manag.* 25(1):65–82.

Hui X (2019) Facilitating Inclusive Global Trade: Evidence from a Field Experiment. *Manage. Sci.* 66(4):1737–1755.

Hunton J, Lippincott B, Reck J (2003) Enterprise Resource Planning Systems: Comparing Firm Performance of Adopters and Nonadopters. *Int. J. Account. Inf. Syst.* 4:165–184.

Ibrahim H, Sorrell S, Nair SC, Al Romaithi A, Al Mazrouei S, Kamour A (2020) Rapid Development and Utilization of a Clinical Intelligence Dashboard for Frontline Clinicians to Optimize Critical Resources During Covid-19. *Acta Inform. Med.* 28(3):209–213.

Jensen R (2007) The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *Q. J. Econ.* 122(3):879–924.

Jin W, McElheran K (2018) Economies Before Scale: Survival and Performance of Young Plants in the Age of Cloud Computing. *SSRN Electron. J.*

Khairat SS, Dukkipati A, Lauria HA, Bice T, Travers D, Carson SS (2018) The Impact of Visualization Dashboards on Quality of Care and Clinician Satisfaction: Integrative Literature Review. *JMIR Hum. factors* 5(2).

Llave MR (2017) Business Intelligence and Analytics in Small and Medium-sized Enterprises: A Systematic Literature Review. *Procedia Comput. Sci.* 121:194–205.

Lu Y, Gupta A, Ketter W, Van Heck E (2019) Information Transparency in Business-to-Business Auction Markets: The Role of Winner Identity Disclosure. *Manage. Sci.* 65(9):4261–4279.

McAfee A, Brynjolfsson E (2012) Big data: The management revolution. *Harv. Bus. Rev.* (October):2–9.

Mithas S, Ramasubbu N, Sambamuthy V (2011) How Information Management Capability Influences Firm Performance. *Manag. Inf. Syst. Q.* 35(1).

Müller O, Fay M, vom Brocke J (2018) The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *J. Manag. Inf. Syst.* 35(2):488–509.

Overby E, Forman C (2015) The effect of electronic commerce on geographic purchasing patterns and price dispersion. *Manage. Sci.* 61(2):431–453.

Pan X, Ratchford BT, Shankar V (2002) Can price dispersion in online markets be explained by differences in e-tailer service quality? *J. Acad. Mark. Sci. 2002 304* 30(4):433–445.

Parker C, Ramdas K, Savva N (2016) Is IT Enough? Evidence from a Natural Experiment in India's Agriculture Markets. *Manage. Sci.* 62(9):2481–2503.

Pauwels K (2014) *It's Not the Size of the Data -- It's How You Use It : Smarter Marketing with Analytics and Dashboards.* (AMACOM).

Porter ME, Millar VA (1985) How information gives you competitive advantage. *Harv. Bus. Rev.* 63:149–160.

Ravi V, Kamaruddin S (2017) Big Data Analytics Enabled Smart Financial Services: Opportunities and Challenges. *Lect. Notes Comput. Sci.* 10721 LNCS:15–39.

Rogers EM (2003) *Diffusion of Innovations* 5th ed. (Free Press).

Rubin DB (2008) For objective causal inference, design trumps analysis. *Ann. Appl. Stat.* 2(3):808–840.

Sharma R, Mithas S, Kankanhalli A (2014) Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. *Eur. J. Inf. Syst.* 23(4):433–441.

Simchi-Levi D, Gadewadikar J, LaFiandra L, McCarthy B (2015) *Winning with Analytics | Accenture*

Simpao AF, Ahumada LM, Gálvez JA, Rehman MA (2014) A review of analytics and clinical informatics in health care. *J. Med. Syst.* 38(4):1–7.

Subramanian H, Overby E (2017) Electronic commerce, spatial arbitrage, and market efficiency. *Inf. Syst. Res.* 28(1):97–116.

Tambe P, Hitt LM (2012) The Productivity of Information Technology Investments: New Evidence from IT Labor Data. *Inf. Syst. Res.* 23(3-part-1):599–617.

Waarts E, Everdingen YM van, Hillegersberg J van (2002) The dynamics of factors affecting the adoption of innovations. *J. Prod. Innov. Manag.* 19(6):412–423.

Yu W, Wong CY, Chavez R, Jacobs MA (2021) Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *Int. J. Prod. Econ.* 236:108135.

Appendix

A1. Seller Experience Survey

A1.1 Section on data and managerial decision making

Managerial decision-making at your eBay store

The following questions address managerial decision-making practices at your eBay store.

In your answers, please refer to managerial decisions regarding:

- Pricing
- Inventory
- Product mix
- Marketing and promotional activities
- Shipping and packaging alternatives
- Any other decisions relevant to your eBay store

❍ Got it. Let's go! *(Note: answer required to ensure reading the above text)*

Q1: What best describes the **availability of data** to support decision making at your store, a year ago and today?

Mark one choice in each row -

	No data available	Small amount of data available	Moderate amount of data available	A great deal of data available	All the data we need available
A year ago	❍	❍	❍	❍	❍
Today	❍	❍	❍	❍	❍

Q2: What best describes the **use of data** for making managerial decisions at your eBay store, a year ago and today?

Mark one choice in each row -

	0%-20% of the time	21%-40%	41%-60%	61%-80%	81%-100% of the time
A year ago, we used data-	❍	❍	❍	❍	❍
Today, we use data-	❍	❍	❍	❍	❍

The following questions address practices for monitoring performance at your eBay store.

Key performance indicators or *KPIs* can refer to the following metrics:

- Dollar amount of sales (overall and per category)
- Listing conversion rates
- Seller rating
- Feedback score
- Procurement costs
- Stock outs
- Handling times (time from order to shipment)
- Shipping times
- Any other performance metrics relevant to your eBay store

❍ Got it. Let's go! *(Note: answer required to ensure reading the above text)*

Q3: What best describes the **number of KPIs monitored** at your eBay store, a year ago and today?

Mark one choice in each row –

	None monitored	1-2 KPIs	3-4 KPIs	5 or more KPIs
A year ago	❍	❍	❍	❍
Today	❍	❍	❍	❍

A2. Seller and Store Characteristics: Variable Definitions

Table A2.1. Variable Definitions for Survey-Based Variables

Variable	Defintion
$dBrickNMortar$	Binary variable indicating whether the seller also operates a brick-and-mortar location.
$dOtherOnlineChannels$	Binary variable indicating whether the seller reports selling in online channels other than eBay.
$numFTEs$	The number of full-time equivalents (FTEs) engaged in eBay selling activities, in one of the categories 0-1, 2-3, 4 or more.
$numLocations$	Number of physical locations used for store operations reported in one of the categories 1, $2-3, 4$ or more.
dEd	Binary variable indicating whether more than 50% of store employees have college education or higher.
$dLearning$	Binary variable indicating whether the seller reported using an above-median number of learning resources on eBay selling, by selecting from a list of common resources. The median respondent selected one learning resource. Further note, that in Section 5.4, the analysis is conducted for a subsample of SH adopters, and the subsample median is 2.
$dStrongQuantPref$	Binary variable indicating a stated preference for quantitative formats of performance reports, over verbal or mixed formats.

A3. Correlations between the Dependent Variables and the Partial Correlation between Feedback and Quantity and between New Listings and Quantity, Controlling for Seller and Week Fixed Effects

The following table reports the correlations between the dependent variables studied.

Table A3.1. Correlation Matrix

	Sales	*Quantity*	*Price*	*Feedback*	*NewListings*
Sales	1	0.366	0.236	0.201	0.195
Quantity	0.366	1	-0.026	0.438	0.544
Price	0.236	-0.026	1	-0.031	-0.015
Feedback	0.201	0.438	-0.031	1	0.258
NewListings	0.195	0.544	-0.015	0.258	1

The high correlation between *Quantity* and both *Feedback* and *NewListings* may suggest that the effect of SH access on these dependent variables is a byproduct of the increase in *Quantity*, rather than a seperate effect of SH on service quality and new listing creation. Addressing this concern, we derive the partial correlation between *Feedback* and *Quantity,* and between *NewListings* and *Quantity*, controlling for seller and week fixed effects, using the following model:

$$DVZ_{sw} = \alpha_s + \beta_w + \boldsymbol{\rho} \cdot QuantityZ_{sw} + \epsilon_{sw}$$

Where DVZ_{sw} is one of $\{FeedbackZ_{sw}, NewListingsZ_{sw}\}$. *FeedbackZ*, *NewListingsZ* and *QuantityZ* are *Feedback*, *NewListings* and *Quantity* transformed to z-scores, such that ρ is the partial correlation of interest. α_s and β_w are fixed effects for seller and week and the idiosyncratic error term is ϵ_{sw} (as in all other models in the paper). Estimation results provided in Table A3.2. show that the partial correlation between *Feedback* and *Quantity* is not statistically significant, while the partial correlation between NewListings and Quantity is both statistically and economically significant.

Considering *Feedback* and *Quantity,* the result of a partial correlation that is not statistically significant suggests that the simple correlation is largely explained by seller and time fixed effects. Since these are controlled for in the estimation of the impact of SH access on *Feedback*, the result of a positive impact of SH on seller feedback holds and is distinct from the effect on quantity sold.

This is not the case for *NewListings* and *Quantity*, and therefore the effect of SH on new listing activity is likely related to the effect on quantity sold, and cannot be identified as a separate effect of SH.

Table A3.2. The Partial Correlation between Feedback and Quantity and between New Listings and Quantity, Controlling for Seller and Week Effects

	Dependent variable:	
	$FeedbackZ$	$NewListingsZ$
	(1)	(2)
$QuantityZ$	-0.002	0.232^{***}
	(0.002)	(0.064)
Observations	4,235,184	4,237,106
Adjusted R^2	0.999	0.394
Note:	Seller and week fixed effects included. Cluster robust standard errors shown in parentheses (Clustered on seller). **** p<0.01, ** p<0.05, * p<0.1*	

A4. Estimation Results of the Relative Time Model

This section presents estimation results of the relative time model (specification (4)) for the effect of SH access on *Sales*, as well as for *Quantity, Price, Feedback,* and *NewListings*, as defined in Section 5.2. Estimation results for the sales impact are reported in column (1) of Table A4.1., discussed in Section 5.1. and depicted in Figure 4. Hence, we focus our discussion here on the dynamic impacts of SH access on *Quantity, Price, Feedback,* and *NewListings* reported in columns (2)-(5) of Table A4.1.

Our estimates point to a positive and increasing effect of SH access on *Quantity, Feedback,* and *NewListings*. The weekly quantity sold increases by 0.8-0.9% in the first three weeks following the opt-in invitation, increasing to 1.3-1.5% in weeks 4-5, and to 2.3-2.8% from week 6 onwards. The dynamic effect on the average price of items sold is not statistically significant at the 5% level, in line with the results reported in Section 5.2. Sellers' feedback scores increase as a result of SH access, by 0.1% in weeks 1-2, and further by 0.2% in the following weeks. The impact on the weekly number of new listings is not statistically significant in weeks 1-4, attains significance in week 5 with an increase of 1.5% in new listing creation, further increasing to 1.9-2.3% in week 6 onwards. The pattern of the delayed dynamic effect on *NewListings* provides further evidence of the link between the SH impact on *Quantity* and on *NewListings*, suggesting that new listings are likely not adding variety, but rather created in response to the increased demand for sellers' existing products.

Finally, we note that the coefficients of the impacts of SH access on all five dependent variables in the weeks preceding ramp-up are not statistically significant, implying that the trends of *Sales*, *Quantity, Price, Feedback,* and *NewListings* of the different ramp-up groups run parallel pre-ramp-up, further validating our empirical strategy.

Table A4.1. The Dynamic Impacts of SH Access - Relative Time Model

	Dependent variable:				
	$\log(Sales)$	$\log(Quantity)$	$\log(Price)$	$\log(Feedback)$	$\log(NewListings)$
	(1)	(2)	(3)	(4)	(5)
$RelWeek(t \leq -8)$	-0.004 (0.009)	-0.005 (0.004)	0.001 (0.004)	-0.001^{*} (0.001)	0.004 (0.005)
$RelWeek(-7)$	-0.005 (0.008)	-0.006 (0.003)	-0.001 (0.004)	-0.001 (0.001)	0.001 (0.004)
$RelWeek(-6)$	-0.0004 (0.008)	-0.003 (0.003)	0.002 (0.004)	-0.001^{*} (0.001)	0.002 (0.004)
$RelWeek(-5)$	0.006 (0.008)	-0.001 (0.003)	-0.001 (0.004)	-0.001 (0.001)	0.002 (0.004)
$RelWeek(-4)$	0.006 (0.007)	-0.0004 (0.003)	0.002 (0.003)	-0.001 (0.0005)	0.003 (0.004)
$RelWeek(-3)$	0.005 (0.007)	-0.002 (0.003)	0.004 (0.003)	-0.0004 (0.0004)	0.002 (0.004)
$RelWeek(-2)$	0.005 (0.006)	-0.001 (0.002)	-0.001 (0.003)	-0.0004 (0.0004)	0.003 (0.003)
$RelWeek(-1)$	-0.002 (0.005)	-0.001 (0.002)	-0.001 (0.003)	-0.0001 (0.0003)	-0.001 (0.003)
$RelWeek(0)$			*Omitted base case*		
$RelWeek(1)$	0.025^{***} (0.006)	0.008^{***} (0.002)	-0.0002 (0.003)	0.001^{***} (0.0004)	0.003 (0.003)
$RelWeek(2)$	0.035^{***} (0.007)	0.009^{***} (0.003)	0.001 (0.004)	0.001^{***} (0.0004)	0.005 (0.004)
$RelWeek(3)$	0.025^{***} (0.008)	0.008^{***} (0.003)	0.002 (0.004)	0.002^{***} (0.001)	0.005 (0.004)
$RelWeek(4)$	0.043^{***} (0.008)	0.013^{***} (0.003)	0.004 (0.004)	0.002^{***} (0.001)	0.005 (0.004)
$RelWeek(5)$	0.049^{***} (0.009)	0.015^{***} (0.004)	0.007^{*} (0.004)	0.002^{***} (0.001)	0.015^{***} (0.005)
$RelWeek(6)$	0.063^{***} (0.009)	0.023^{***} (0.004)	0.008^{*} (0.004)	0.002^{***} (0.001)	0.019^{***} (0.005)
$RelWeek(7)$	0.059^{***} (0.010)	0.023^{***} (0.004)	0.003 (0.004)	0.002^{***} (0.001)	0.023^{***} (0.005)
$RelWeek(t \geq 8)$	0.074^{***} (0.011)	0.028^{***} (0.005)	0.005 (0.005)	0.002 (0.001)	0.023^{***} (0.006)
Observations	4,237,106	4,237,106	3,193,034	4,235,184	4,237,106
Adjusted R^2	0.640	0.818	0.655	0.995	0.616
Note:	Seller and week fixed effects included.				
	Cluster robust standard errors shown in parentheses (Clustered on seller).				
	**** p<0.01, ** p<0.05, * p<0.1*				

A5. Robustness Tests

A5.1. Robustness of DDD metrics

Our DDD metrics are constructed following Brynjolfsson and McElheran (2016, 2019), and thus the DDD indicator is defined based on reported data availability, use and monitoring extent, and the DDD index is defined as an unweighted average of these three components after normalization to $[0{,}10]$. Yet, one may argue that data availability does not necessarily lead to DDD. Furthermore, even if all three components are included in the definition of the DDD metrics, it is not clear that they should be weighted equally, as they differ in mean and variance.

We therefore test three alternative definitions of our DDD metrics. First, we construct both the DDD indicator and index based on reported data use and performance monitoring alone, denoting these by $\mathbb{I}_{DDD_2}$ and DDD_2. The two-variable indicator equals 1 for respondents reporting high data use (responses in the top 2 categories), as well as high monitoring extent (the top category: tracking at least 5 KPIs). The two-variable DDD index is the sum of normalized data use and monitoring scores, scaled to the [0,10] interval. We then construct an alternative version of the DDD index, as the average of standardized scores for the three DDD components (data availability, use, and monitoring), denoted DDD_Z. Using standardized scores, the components now have equal mean and variance.

We repeat the analysis in Section 3.3, estimating specification (1) for these alternative DDD metrics, reporting the results in Table A5.1.1. Our results are qualitatively similar to those reported in Section 3.3, showing a positive and statistically significant association between SH adoption and increases in DDD. SH adopters are over 140% more likely than non-adopters to become data-driven decision makers, as represented by the two-variable DDD indicator (columns (1) and (4)). Furthermore, SH adopters show larger increases in their DDD index than non-adopters, and the results with DDD_2 (columns (2) and (5)) are very similar in magnitude to those derived with the three-component DDD index. Finally, examining increases in DDD_Z, we find that SH adoption is associated with increases in DDD that are 0.22-0.25 standard deviations larger than those of non-adopters. Overall, these results attest to the robustness of our DDD metrics, and further help substantiate our claim that SH is a DDD-enhancing tool.

Table A5.1.1. SH Adoption and Changes in Alternative Definitions of the DDD Metrics

	Dependent variable:					
	$d\mathbb{I}_{DDD_2}$	ΔDDD_2	ΔDDD_Z	$d\mathbb{I}_{DDD_2}$	ΔDDD_2	ΔDDD_Z
	logistic	*OLS*		*logistic*	*OLS*	
	(1)	(2)	(3)	(4)	(5)	(6)
dSH	0.91**	0.95***	0.25***	0.88**	0.79**	0.22**
	(0.39)	(0.28)	(0.08)	(0.44)	(0.32)	(0.09)
$dLearning$				1.68***	0.72**	0.15
				(0.46)	(0.33)	(0.09)
dEd				-0.57	-0.14	0.06
				(0.41)	(0.32)	(0.09)
$dStrongQuantPref$				-0.51	-0.06	0.02
				(0.42)	(0.32)	(0.09)
$dOtherOnlineChannels$				0.16	-0.37	-0.10
				(0.41)	(0.33)	(0.09)
$dBrickNMortar$				-0.07	0.33	-0.02
				(0.59)	(0.44)	(0.12)
$numFTEs(M)$				0.23	0.29	0.03
				(0.46)	(0.37)	(0.10)
$numFTEs(L)$				-1.00	0.43	0.24
				(0.88)	(0.58)	(0.16)
$numLocations(2-3)$				-0.26	0.09	0.01
				(0.47)	(0.38)	(0.10)
$numLocations(4\ or\ more)$				-0.93	-1.02	-0.10
				(1.16)	(0.90)	(0.25)
$Constant$	-2.57***	1.24***	-0.14**	-2.92***	1.18***	-0.17*
	(0.33)	(0.20)	(0.06)	(0.55)	(0.37)	(0.10)
Observations	304	304	304	260	260	260
Adjusted R^2		0.03	0.03		0.03	0.02
Log Likelihood	-107.63			-85.68		
Akaike Inf. Crit.	219.26			193.36		
F Statistic		11.42*** (df = 1; 302)	11.16*** (df = 1; 302)		1.77* (df = 10; 249)	1.64* (df = 10; 249)
Note:	**** p<0.01, ** p<0.05, * p<0.1*					

Another possible concern regarding our definition of the DDD indicator is that it considers high data availability and use as represented by responses in the top two categories, whereas high monitoring extent is represented by responses in the top category alone.[45] We address this concern by constructing one final alternate DDD indicator, which considers high levels of all three DDD components as represented by their top two response categories. We define $\mathbb{I}_{DDD_{Top2Cat}}$ to equal 1 for respondents reporting data availability and use in the top two categories, as well as monitoring extent in the top two categories (namely, tracking 3-4 KPIs or at least 5 KPIs), and 0 otherwise.

We now estimate specification (1) for $\mathbb{I}_{DDD_{Top2Cat}}$, reporting the results in Table A5.1.2. Again, our results are qualitatively similar to those reported in Section 3.3, as SH adopters are over 129% more likely than non-adopters to become data-driven decision makers, as represented by this alternative DDD indicator. Our DDD indicator is therefore robust to this alternative definition as well.

[45] This is to maintain consistency and comparability with the definitions of DDD in Brynjolfsson and McElheran (2016, 2019).

Table A5.1.2. SH Adoption and Changes in an Alternative DDD Indicator, based on the Top 2 Categories of all Three Components

	Dependent variable:	
	$d\mathbb{I}_{DDD_{Top2Cat}}$	
	Main spec.	Additional controls
	(1)	(2)
dSH	0.83**	1.01***
	(0.32)	(0.36)
$dLearning$		0.35
		(0.34)
dEd		-0.26
		(0.33)
$dStrongQuantPref$		-0.28
		(0.34)
$dOtherOnlineChannels$		-0.23
		(0.34)
$dBrickNMortar$		-0.70
		(0.52)
$numFTEs(M)$		0.14
		(0.39)
$numFTEs(L)$		0.29
		(0.60)
$numLocations(2-3)$		-0.11
		(0.39)
$numLocations(4\ or\ more)$		-1.05
		(1.14)
$Constant$	-2.06***	-1.77***
	(0.27)	(0.40)
Observations	304	260
Log Likelihood	-137.18	-120.12
Akaike Inf. Crit.	278.36	262.23
Note:	**** p<0.01, ** p<0.05, * p<0.1*	

A5.2. Balance of ramp-up groups

Figure A5.2.1 below depicts the distribution of annual sales in 2015, the year prior to the SH launch, for each ramp-up group in Figure A5.2.1 below using boxplots. For each seller group, the rectangle ("box") graphed represents the first to third quartile of the log of annual sales ($Q1$ to $Q3$ as the bottom to top sides of the rectangle), and the black horizontal line inside the rectangle represents the median of the distribution. The vertical lines extending from the bottom and top of each rectangle are the "whiskers". The bottom whisker depicts the bottom quartile, ending in the minimum of the distribution, which is the same for all groups, as we focus on sellers with annual sales of at least 10,000 USD in 2015. The top whisker ranges from the third quartile ($Q3$) to the value of $Q3 + 1.5 \cdot IQR$, where $IQR = Q3 - Q1$. Values above $Q3 + 1.5 \cdot IQR$ are considered outliers and depicted as dots.

The figure shows that the ramp groups have largely similar distributions of annual sales in 2015, with differences mainly in the sizes of very large sellers assigned to each group (the outliers).

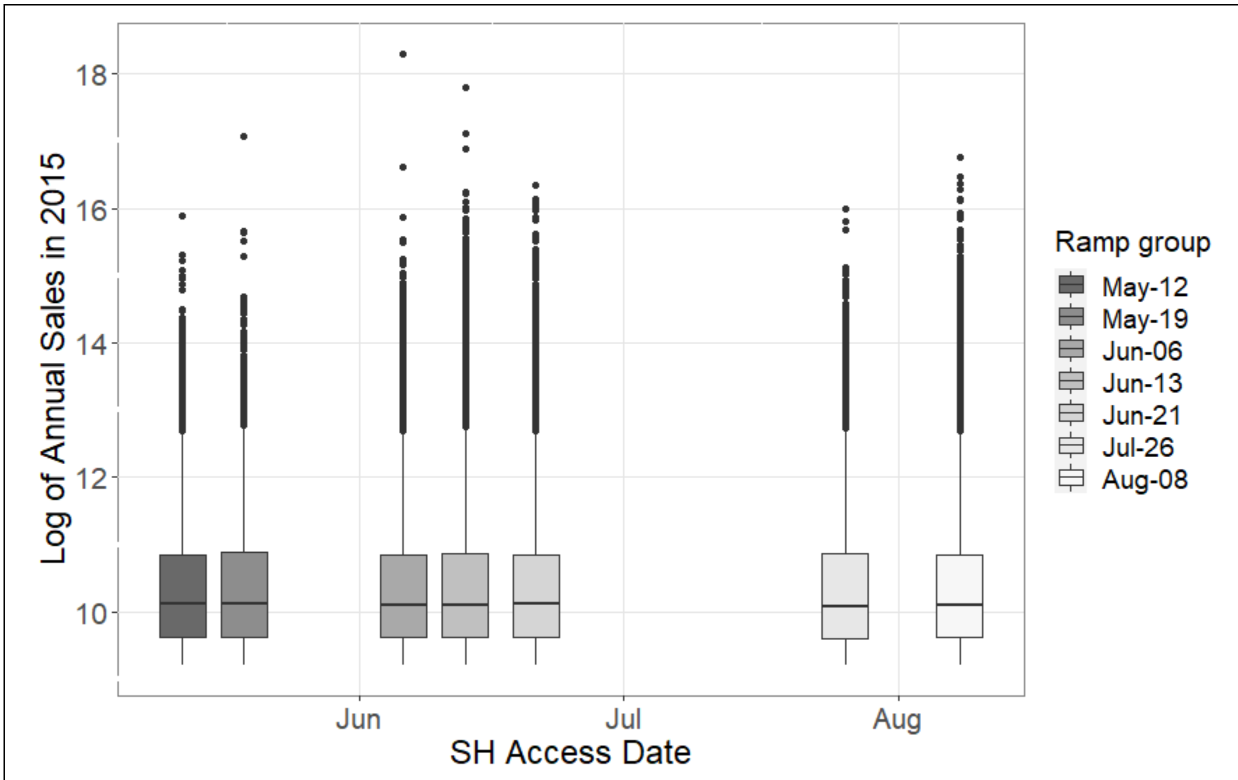

Figure A5.2.1. The Distribution of Annual Sales in the Year Prior to SH's Introduction, for each Ramp-Up Group.

A5.3. Testing the parallel trends assumption

Table A5.3.1. reports the estimation results of specification (7), which directly tests the parallel trends assumption. Note that β_2, the coefficient of the interaction $RampGroup \times Trend$ is not significantly different from 0 in all six estimations, comparing each ramp-up group, in turn, to the Aug. 8 group.

Table A5.3.1. Pre-Trend Relative to the Aug. 8 Group: Each Group Separately

	Dependent variable:					
	log($Sales$)					
	May12	May19	Jun06	Jun13	Jun21	Jul26
	(1)	(2)	(3)	(4)	(5)	(6)
$Trend$	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$RampGroup \times Trend$	0.001	0.002	-0.001	0.001	0.002	0.003
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
Observations	626,040	623,190	695,160	1,111,990	943,520	657,470
Adjusted R^2	0.67	0.67	0.67	0.67	0.67	0.67

Note: Seller level fixed effects included.
Cluster robust standard errors shown in parentheses (Clustered on seller).
**** p<0.01, ** p<0.05, * p<0.1*

A5.4. Verifying that the results are not driven by a specific ramp-up group

Tables A5.4.1 and A5.4.2 report estimation results for our main specifications, models (2) and (4), omitting one ramp-up group at a time, demonstrating that our results are thus not driven by a specific ramp-up group.

Table A5.4.1. The Impact of SH on Sales: ITT Estimates Omitting One Group at a Time

	Dependent variable:					
	log ($Sales$)					
	Omit May12	Omit May19	Omit Jun06	Omit Jun13	Omit Jun21	Omit Jul26
	(1)	(2)	(3)	(4)	(5)	(6)
$SHaccess$	0.04***	0.04***	0.04***	0.04***	0.03***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	4,092,183	4,098,738	3,933,207	2,974,498	3,361,979	4,019,894
Adjusted R^2	0.64	0.64	0.64	0.64	0.64	0.64

Note: Seller and week fixed effects included.
Cluster robust standard errors shown in parentheses (Clustered on seller).
**** p<0.01, ** p<0.05, * p<0.1*

Table A5.4.2. The Dynamic Impact of SH on Sales: Relative Time Model Omitting One Group at a Time

	Dependent variable:					
	$\log(Sales)$					
	Omit May12	Omit May19	Omit Jun06	Omit Jun13	Omit Jun21	Omit Jul26
	(1)	(2)	(3)	(4)	(5)	(6)
$RelWeek(t \leq -8)$	-0.01	-0.01	-0.01	0.01	0.001	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-7)$	-0.01	-0.01	-0.01	-0.01	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-6)$	-0.002	-0.003	-0.002	0.01	0.0002	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-5)$	0.004	0.004	0.01	0.02^{*}	0.01	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-4)$	0.01	0.004	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-3)$	0.004	0.002	0.003	0.02^{**}	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-2)$	0.004	0.0001	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(-1)$	-0.003	-0.005	-0.001	0.01	-0.004	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(0)$			Omitted base case			
$RelWeek(1)$	0.02^{***}	0.02^{***}	0.03^{***}	0.04^{***}	0.03^{***}	0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(2)$	0.03^{***}	0.04^{***}	0.04^{***}	0.04^{***}	0.03^{***}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(3)$	0.03^{***}	0.02^{***}	0.02^{***}	0.03^{***}	0.03^{***}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(4)$	0.05^{***}	0.04^{***}	0.05^{***}	0.05^{***}	0.04^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(5)$	0.05^{***}	0.05^{***}	0.05^{***}	0.06^{***}	0.04^{***}	0.06^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(6)$	0.07^{***}	0.06^{***}	0.07^{***}	0.08^{***}	0.06^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(7)$	0.06^{***}	0.06^{***}	0.06^{***}	0.07^{***}	0.05^{***}	0.06^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$RelWeek(t \geq 8)$	0.07^{***}	0.08^{***}	0.07^{***}	0.09^{***}	0.07^{***}	0.08^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	4,092,183	4,098,738	3,933,207	2,974,498	3,361,979	4,019,894
Adjusted R^2	0.64	0.64	0.64	0.64	0.64	0.64
Note:	Seller and week fixed effects included.					
	Cluster robust standard errors shown in parentheses (Clustered on seller).					
	**** p<0.01, ** p<0.05, * p<0.1*					

A5.5. The impact of SH access: Recently proposed estimators for staggered treatment effects

While the randomization of sellers into ramp-up groups, and the existence of a large group of not-yet treated sellers in our period of analysis alleviate most bias concerns raised in the recent DiD literature, we, nevertheless, test the robustness of our estimates using recently proposed estimators for the generalized DiD setting (see survey by Roth et al. 2022).

Our result of the effect of SH access on sales is derived from the estimation of the generalized DiD specification (2), in which the timing of treatment varies between ramp-up groups. The estimator for the SH access effect, known as the two-way fixed effects (TWFE) estimator, may be biased if there exists treatment effect heterogeneity across ramp-up groups or over time. We note that heterogeneity between ramp-up groups is ruled out due to the random assignment of sellers to ramp-up groups. Yet, heterogeneity over time cannot be ruled out, as estimation results of the relative time model (4) suggest that the SH impact strengthens over time.[46] Hence, we estimate the effect of SH access using three new heterogeneity-robust estimators for models with staggered treatment timing, proposed by Callaway and Sant'Anna (2021), Roth and Sant'Anna (2021), Sun and Abraham (2021).

We find that our estimate of the average effect of SH access on the log of sales of 0.03482 (Section 5.1) is highly similar to the Callaway and Sant'Anna and Sun and Abraham estimators of 0.03671 and 0.03699, and that the Roth and Sant'Anna estimator suggests an even stronger SH impact at 0.07051. Figure A5.5.1. compares these estimators, which add robustness to our main result.

[46] The estimation results of the relative time model are not biased, since randomization into ramp-up groups implies homogeneity of the average treatment effect across groups.

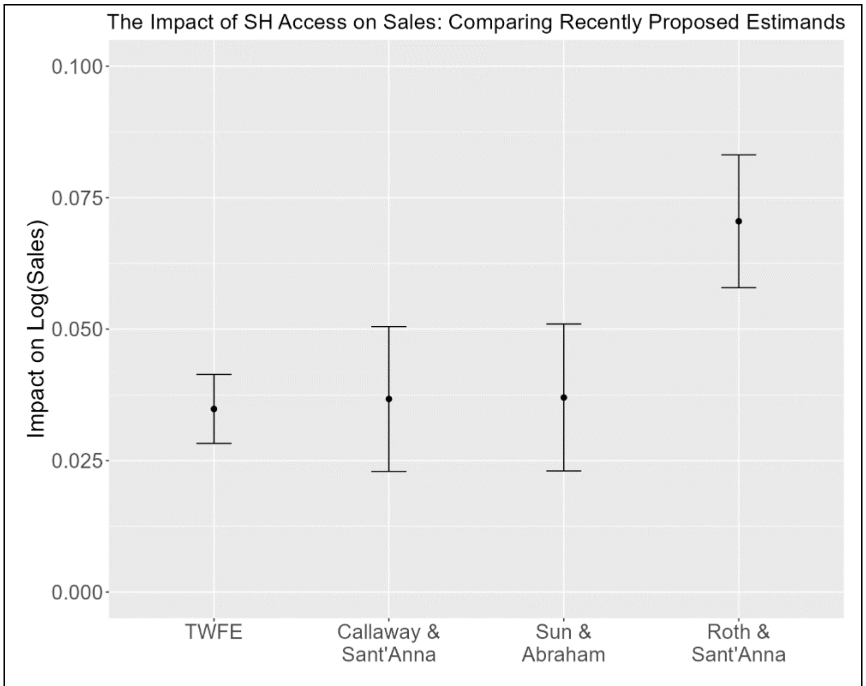

Figure A5.5.1. The estimated SH access effect of sales: Comparing the TWFE estimator to recently proposed estimators.

A5.5.1 References

Callaway B, Sant'Anna PHC (2021) Difference-in-Differences with multiple time periods. J. Econom. 225(2):200–230.

Roth J, Sant'Anna PHC (2021) Efficient Estimation for Staggered Rollout Designs

Roth J, Sant'Anna PHC, Bilinski A, Poe J (2022) What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature.

Sun L, Abraham S (2021) Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. J. Econom. 225(2):175–199.

A5.6. The SH impact by seller size

Table A5.6.1. The Impact of SH Access on Sales in each Seller Segment

	Dependent variable:			
	$\log(Sales)$	ComplyAnytime	$\log(Sales)$	
	ITT	First stage	TOT IV	TOT Adopters
	(1)	(2)	(3)	(4)
Panel A. Entrepreneurs				
$SHaccess$	0.03^{***}	0.29^{***}		0.04^{***}
	(0.01)	(0.001)		(0.01)
$SHadoption$(fitted)			0.12^{***}	
			(0.02)	
Observations	3,801,279	3,801,279	3,801,279	757,965
Adjusted R^2	0.59	0.48	0.59	0.55
Panel B. Merchants				
$SHaccess$	0.04^{**}	0.36^{***}		0.03
	(0.02)	(0.004)		(0.03)
$SHadoption$(fitted)			0.10^{**}	
			(0.05)	
Observations	409,722	409,722	409,722	99,452
Adjusted R^2	0.77	0.52	0.77	0.74
Panel C. Large Merchants				
$SHaccess$	0.03	0.39^{***}		-0.02
	(0.07)	(0.02)		(0.09)
$SHadoption$(fitted)			0.08	
			(0.17)	
Observations	26,105	26,105	26,105	7,268
Adjusted R^2	0.87	0.53	0.87	0.83

Note: Seller and week fixed effects included.
Cluster robust standard errors shown in parentheses (Clustered on seller).
**** p<0.01, ** p<0.05, * p<0.1*

A5.7. The SH impact in homogeneous vs. differentiated product categories

A5.7.1. Defining main categories as homogeneous or differentiated

Auto-tagged ePIDs were added to eBay's listing data in September 2017, and were thus not available in the year of SH's roll-out. We, therefore, calculate the percent of listings with auto-tagged ePIDs in each main category, for all listings posted on eBay between January 1st and 7th , 2023. Results are reported in Table A5.7.1. below in descending order of percent of auto-tagged ePIDs. We define the top four main categories in terms of availability of auto-tagged ePIDs as homogeneous categories, and the bottom four categories as differentiated.

Table A5.7.1. Percent of Listings with an Auto-Tagged ePID, by Main Category, January 1-7, 2023.

Main Category	% Auto-tagged ePID
Media	58.6%
Parts & Accessories	45.5%
Electronics	32.0%
Business & Industrial	22.9%
Home & Garden	16.4%
Lifestyle	14.4%
Collectibles	5.8%
Fashion	5.7%

A5.7.2. The SH impact in homogeneous vs. differentiated product categories: Robustness tests

In Section 5.2 we define $MainCategory_{sw}$ as the product category in which seller s had the highest revenue in week w, yet this may lead to cases where $MainCategory_{sw}$ is determined by a few expensive items, whereas the majority of seller s's transactions are of low priced items in another category. We therefore test the robustness of our findings by employing a quantity-based definition of sellers' main category. We define $MainCategoryQ_{sw}$ as the product category in which seller s sold the largest number of items in week w. We then define the indicator $HomogQ_{sw}$ to equal 1 when $MainCategoryQ_{sw}$ is one of the homogeneous categories defined in A5.7.1., and 0 otherwise. We note that the correlation between $HomogQ$ and $Homog$ is extremely high, with $\rho = 0.86$, and that 17.87% of our panel consists of sales in homogeneous main categories using the quantity based definition, compared to 17.21% using the revenue based definition. This implies that the case where $MainCategory_{sw}$ is biased due to a small number of highly priced items is quite rare.

We repeat the analysis in Section 5.2, estimating specification (5) with $HomogQ$ instead of $Homog$. The results, reported in Table 5.7.2., are qualitatively similar to the results obtained with $Homog$. Focusing on the interaction coefficient, we note that weekly sales for sellers in homogeneous categories increase by 19.5% more than the sales of their non-homogeneous counterparts as a result of SH access, based on the estimation with $HomogQ$ compared to an estimate of 13.9% using $Homog$. The quantity increase for sellers in homogeneous categories is 5.4% higher than for sellers in non-homogeneous categories using $HomogQ$, compared to 4.1% with $Homog$. The interaction effect on average prices is 1.1%, 1.8% for the effect on feedback, and 2% for the number of new listings with $HomogQ$, compared to effects of 0.8%, 1.6% and 1.3% (respectively) estimated with $Homog$.

Table 5.7.2. The Effect of SH Access, by Homogeneity of Product Category, using a Quantity-Based Definition

	Dependent variable:				
	$\log(Sales)$	$\log(Quantity)$	$\log(Price)$	$\log(Feedback)$	$\log(NewListings)$
	(1)	(2)	(3)	(4)	(5)
$SHaccess$	-0.003	0.002	-0.0005	-0.002^{***}	0.005^{*}
	(0.006)	(0.002)	(0.002)	(0.001)	(0.003)
$HomogQ$	2.409^{***}	0.641^{***}	-0.026^{***}	0.001	0.249^{***}
	(0.011)	(0.004)	(0.003)	(0.0005)	(0.003)
$SHaccess \times HomogQ$	0.178^{***}	0.053^{***}	0.011^{***}	0.018^{***}	0.020^{***}
	(0.007)	(0.003)	(0.003)	(0.001)	(0.005)
Observations	4,237,106	4,237,106	3,193,034	4,235,184	4,237,106
Adjusted R^2	0.675	0.826	0.655	0.995	0.617
Note:	Seller and week fixed effects included.				
	Cluster robust standard errors shown in parentheses (Clustered on seller).				
	$^{***}p<0.01, ^{**}p<0.05, ^{*}p<0.1$				

Further testing the robustness of our results, we estimate specification (5) for a subsample of sellers who specialize in a single product category, for whom the definition of $HomogQ$ is cleaner. We define specialization by first calculating each seller's share of items sold in $MainCategoryQ_{sw}$ in each week. We then compute sellers' average share of items in $MainCategoryQ_{sw}$ over all weeks of activity, and consider specialized sellers as those with an average at or above 0.9. The resulting subsample consists of 133,914 specialized sellers, approximately 73% of our original sample. Estimation results for this subsample are reported in Table 5.7.3. Again, focusing on the interaction coefficient representing the differential effect of SH access for sellers specializing in homogeneous product categories over those specializing in nonhomogeneous categories, we find that the effect is qualitatively similar, and mostly stronger for this subsample of sellers, providing additional evidence of the robustness of the results in Section 5.2.

Table 5.7.3. The Effect of SH Access, by Homogeneity of Product Category, using a Quantity-Based Definition, for a Subsample of Specialized Sellers

	Dependent variable:				
	$\log(Sales)$	$\log(Quantity)$	$\log(Price)$	$\log(Feedback)$	$\log(NewListings)$
	(1)	(2)	(3)	(4)	(5)
$SHaccess$	-0.008	0.0002	0.0003	-0.002***	0.005
	(0.007)	(0.003)	(0.003)	(0.001)	(0.003)
$HomogQ$	3.766***	0.979***	-0.031***	-0.0001	0.365***
	(0.013)	(0.005)	(0.006)	(0.001)	(0.004)
$SHaccess \times HomogQ$	0.255***	0.073***	0.010**	0.020***	0.029***
	(0.008)	(0.004)	(0.004)	(0.001)	(0.006)
Observations	3,080,022	3,080,022	2,250,346	3,078,438	3,080,022
Adjusted R^2	0.655	0.813	0.664	0.995	0.608
Note:	Seller and week fixed effects included.				
	Cluster robust standard errors shown in parentheses (Clustered on seller).				
	*** $p<0.01$, ** $p<0.05$, * $p<0.1$				

As a final robustness test, we repeat the estimation, now focusing on specialized sellers whose main category is Media, the most homogeneous category by share of listings with an auto-tagged ePID, compared to those whose main category is Fashion, the least homogeneous category according to this metric. We thus further refine the subsample of specilazed sellers to focus on sellers for whom $MainCategoryQ_{sw} \in \{"Media", "Fashion"\}$. This yields a subsample of 43,552 sellers. Estimation results for this subsample, reported in Table 5.7.4., show that the interaction effect on sales, quantity and price is statistically significant and qualitatively similar to the above reported results (Tables 4, A5.7.2., and A5.7.3.), whereas the effect on feedback and new listing creation is not statistically significant in this smaller sample.

Taken together, this series of robustness tests support our finding that the impact of SH access is stronger for sellers who are active in homogeneous product categories, compared to sellers in non-homogeneous categories.

Still, we acknowledge that the assignment of product category at the seller-week level (as per the structure of our data) and furthermore, our definition of homogeneity at the product category level remain noisy. A more precise estimation of the impact of analytics in homogeneous vs. differentiated product markets is left for future work.

Table 5.7.4. The Effect of SH Access, by Homogeneity of Product Category, using a Quantity-Based Definition, for a Subsample of Specialized Sellers whose Main Category is Media or Fashion

	Dependent variable:				
	$\log(Sales)$	$\log(Quantity)$	$\log(Price)$	$\log(Feedback)$	$\log(NewListings)$
	(1)	(2)	(3)	(4)	(5)
$SHaccess$	0.014	0.004	0.001	0.002	0.012^{**}
	(0.012)	(0.005)	(0.004)	(0.001)	(0.006)
$HomogQ$	3.200^{***}	1.136^{***}	-0.071^{***}	0.001	0.463^{***}
	(0.034)	(0.017)	(0.016)	(0.002)	(0.015)
$SHaccess \times HomogQ$	0.327^{***}	0.108^{***}	0.053^{***}	-0.001	0.012
	(0.017)	(0.010)	(0.009)	(0.003)	(0.013)
Observations	1,001,696	1,001,696	774,637	1,001,242	1,001,696
Adjusted R^2	0.626	0.814	0.695	0.995	0.619
Note:	Seller and week fixed effects included.				
	Cluster robust standard errors shown in parentheses (Clustered on seller).				
	**** p<0.01, ** p<0.05, * p<0.1*				

A6. The Impact of Support Programs for Small Businesses

The potential of analytics tools for small businesses support can be assessed in comparison to the effects of existing programs designed to foster SME revenue growth and survival. A recent meta-analysis has found that interventions supporting SMEs increase firm performance by 7.6%, on average (Cravo and Piza 2019), yet there exists substantial heterogeneity in the impacts of different programs, including evidence of null effects for some (Dvouletý et al. 2021). Grant programs increased SMEs' revenues by 8-10% in Italy (Bernini and Pellegrini 2011), by 17% in Estonia (Hartšenko and Sauga 2013), and by 8-10% for women entrepreneurs in Croatia (Srhoj et al. 2019). Furthermore, investment subsidies have been found to increase sales revenue by 6.5-8% in Italy (Cerqua and Pellegrini 2014), by 12% in Sweden (Söderblom et al. 2015), and by 19% in Belgium for very small firms (Decramer and Vanormelingen 2016). On the other hand, several studies have found null effects on revenue: Grant aid had no effect on SMEs' revenue, while increasing employment growth, in Ireland (Roper and Hewitt-Dundas 2001), and similar results have been found in England for a program offering consultancy services (Mole et al. 2009), as well as for a grant program in Germany (Brachert et al. 2018). Finally, studying R&D grants in the US SME sector as part of the Small Business Innovation Research (SBIR) program, Wallsten (2000) found that these grants completely crowd out firm-financed R&D.

A6.1. References on small business support programs

Bernini C, Pellegrini G (2011) How are growth and productivity in private firms affected by public subsidy? Evidence from a regional policy. *Reg. Sci. Urban Econ*. 41(3):253–265.

Brachert M, Dettmann E, Titze M (2018) Public Investment Subsidies and Firm Performance-Evidence from Germany. *Jahrb. Natl. Okon. Stat.* 238(2):103–124.

Cerqua A, Pellegrini G (2014) Do subsidies to private capital boost firms' growth? A multiple regression discontinuity design approach. *J. Public Econ*. 109:114–126.

Cravo TA, Piza C (2019) The impact of business-support services on firm performance: a meta-analysis. *Small Bus. Econ*. 53(3):753–770.

Decramer S, Vanormelingen S (2016) The effectiveness of investment subsidies: evidence from a regression discontinuity design. *Small Bus. Econ*. 47(4):1007–1032.

Dvouletý O, Srhoj S, Pantea S (2021) Public SME grants and firm performance in European Union: A systematic review of empirical evidence. *Small Bus. Econ.* 57(1):243–263.

Hartšenko J, Sauga A (2013) The role of financial support in SME and economic development in Estonia. *Bus. Econ. Horizons* 9(2):10–22.

Mole KF, Hart M, Roper S, Saal DS (2009) Assessing the Effectiveness of Business Support Services in

England: Evidence from a Theory-Based Evaluation. *Int. Small Bus. J. Res. Entrep.* 27(5):557–582.

Roper S, Hewitt-Dundas N (2001) Grant Assistance and Small Firm Development in Northern Ireland and the Republic of Ireland. Scott. *J. Polit. Econ*. 48(1):99–117.

Söderblom A, Samuelsson M, Wiklund J, Sandberg R (2015) Inside the black box of outcome additionality: Effects of early-stage government subsidies on resource accumulation and new venture performance. *Res. Policy* 44(8):1501–1512.

Srhoj S, Skrinjari B, Radas S, Walde J (2019) Closing the Finance Gap by Nudging: Impact Assessment of Public Grants for Women Entrepreneurs

Wallsten SJ (2000) The Effects of Government-Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program. *RAND J. Econ.* 31(1):82.