Who Wants to Improve their Management? Evidence from A Failed Experiment

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Abstract

Structured management practices are robustly associated with superior performance, but wide dispersion of management quality persists over time, and sign-up to even free management training programmes is abysmally low. So why do many firms seemingly leave money on the table? We design three linked data collection tools to understand this puzzle. We provide the first evidence that firms signing up to management training are strongly positively selected on their existing management practices. This means that firms most in need of improvement are never reached in the first place. Linking novel evidence on firms' intentions and actions, we additionally document that there are two distinct groups of never-treated firms: those held back by lacking *awareness* of their learning needs, and those facing time and capacity *constraints*. Our findings have wide-ranging implications for the design, evaluation and scale-up of business training programmes.

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Keywords: management practices; learning; diffusion; business training

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1 Introduction

Professional management practices have widely been shown to correlate with positive outcomes such as higher firm survival, greater productivity, more innovation, and the ability to forecast the future more accurately (Bertrand and Schoar, 2003; Bloom et al., 2007, 2021). Much of this is causal: when management practices are varied experimentally (Bloom et al., 2013) or quasi-experimentally via institutional interventions such as WWII training programmes (Bianchi and Giorcelli, 2022) and the Marshall Plan (Giorcelli, 2019), profits, productivity and turnover growth increase by magnitudes that are statistically and economically significant. Recent studies (Anderson and McKenzie, 2022; Bruhn and Piza, 2022; Iacovone et al., 2022; Anderson and McKenzie, 2021; McKenzie, 2021; Bruhn et al., 2018; McKenzie and Woodruff, 2014; Bloom et al., 2013) shows that bespoke training by management consultants increases firm performance by 5 to 10 percent.

Despite the demonstrated effects of structured management, management practices continue to vary persistently and systematically across firms. Bloom and Van Reenen (2007)'s landmark paper shows that there are important differences across countries (US firms are on average better managed than European firms) and within countries (most countries and industries display a long tail of badly managed firms). Figure 1 replicates this finding with our data and shows that the wide dispersion of UK management practices has not changed between 2016 and 2020.[1] Bloom and Van Reenen (2010) and Bloom et al. (2017) show these differences in management practices are associated at the country and firm level with performance differences.

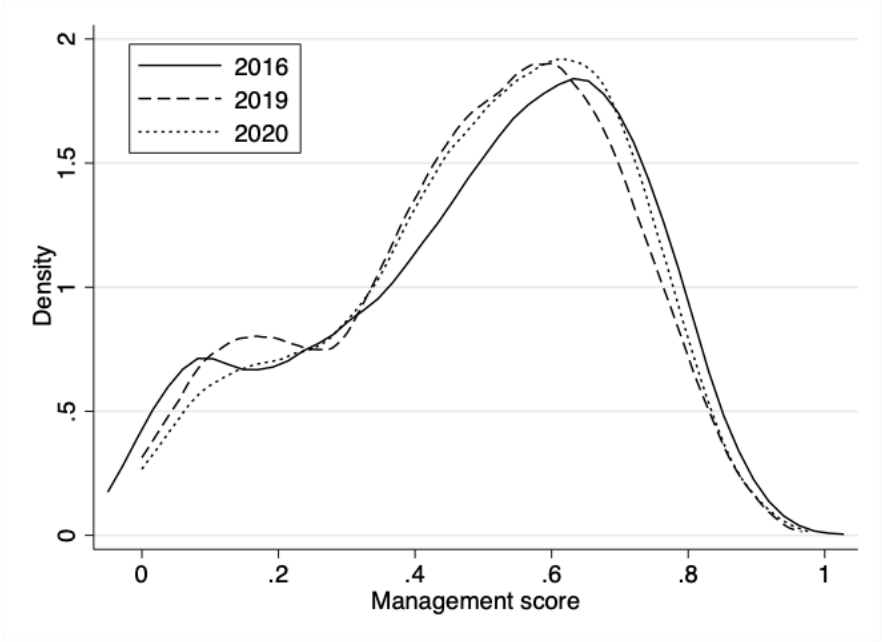
Additionally, there is widespread evidence that even take-up of even free and high-quality management training and mentoring programmes is abysmally low.[2] To give just one example, in 2021, the UK government launched its flagship Help to Grow programme, which provides free training to help small-and-medium-enterprise (SME) business leaders improve their management, seize investment opportunities and grow their business. Less than 10% of target enrolled (BeTheBusiness, 2023).[3]

[1] ONS (2021) provides additional detail for the UK. Much of the variation in management quality is present even within industries, regions and firm size bands.

[2] This reflects an insight in Bruhn et al. (2010) and Bruhn et al. (2018) that while missing managerial capital may hinder the growth of enterprises, the challenge is often to discover effective means to transfer management knowledge to firms. The large literature cited above does this by exploring the uptake of training, consultancy, free information, insourcing and outsourcing.

[3] Many other examples exist. For instance, in 2019, the Innovation Growth Lab at NESTA (Phipps and Fuller, 2022) reference a programme to encourage SMEs in London's retail and hospitality sectors to adopt the use of new technologies. They report that only 43 out of 500 targeted businesses (8.6%) answered the final survey. For more systematic evidence, see Bruhn and Piza (2022).

Figure 1: Overall management practices in 2016, 2019 and 2020

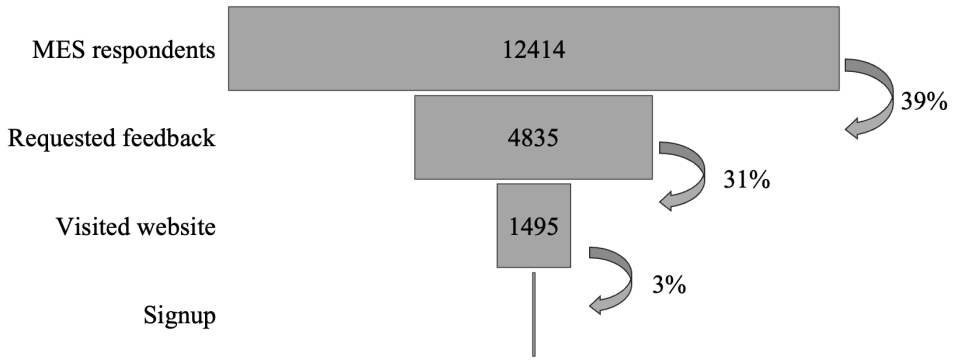


In this paper we therefore examine this puzzle: If management practices can reliably bring about performance improvements, why do so many badly-managed firms persist, and why is take-up of (even free) management training programmes so low?

We designed and implemented a management practices improvement programme to take firms on a journey offering free information and mentoring. Firms were first invited to take part in a voluntary management practices survey administered through the UK's Office for National Statistics (ONS). Respondents could request feedback on their management practices compared to other firms in the same industry and region. The feedback included a link to a website with further free information about their performance and an offer to sign up for free management mentoring, delivered by a recognised UK business training programme. We are able to track respondents in detail through the different stages of this journey.

Figure 2 shows the outcome in the form of a leaky pipeline: consistent with evidence from other business training programmes, very few firms follow the journey to the end point by signing up on the management mentoring programme, even though it is offered for free. At every stage of the process we observe that a significant proportion of firms declined our offer to improve their management. Out of 12,414 respondents to the survey, details of which are given below, just 39% requested feedback on their management score. Only 31% of those firms visited the website providing the information and just 3% of those ultimately signed up for the free mentoring programme offered

Figure 2: Mentoring scheme: the leaky pipeline



by the UK government-sponsored body *Be The Business*. The last section of this pipeline towards improvement is the leakiest of all.

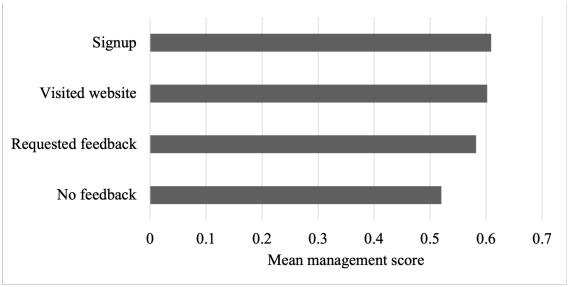
But given our design of the pipeline, we can show that take-up is not just low, it is also highly selective. As Figure 3 shows, that the firms with most to gain (those with the lowest management scores) are least interested in learning how to improve their management. This pattern holds in the aggregate, Panel (a), as well as by size, industry and location, Panels (b)-(d). Already strong performers show more interest in learning, for example, by requesting feedback. In a twist of fate, our earlier attempt to give survey respondents feedback in 2016 failed due to a clerical error. This allows us to examine how a firm's *intention* to improve is associated with subsequent improvement, separate from any *information treatment*.[4]

The key contribution of this paper lies in the novel data it brings to bear on an important debate. This data is in turn the result of three complementary, newly designed data collection tools linkable, and linked, at the firm level to existing microdata. First, together with the UK Office for National Statistics (ONS), we designed the Management and Expectations Survey (MES). The MES is part of the wider global family of management surveys spawned by the work of Bloom et al. (2007) and collects standardised management practices data for over 9,000 British firms in 2016, 12,000 firms in 2019 and 2020 and 14,000 firms in 2023. We designed the survey to track the same firms across years. For roughly 2,500 of these firms, we are able to link responses across waves, allowing longer comparisons through time *within the same firm*.

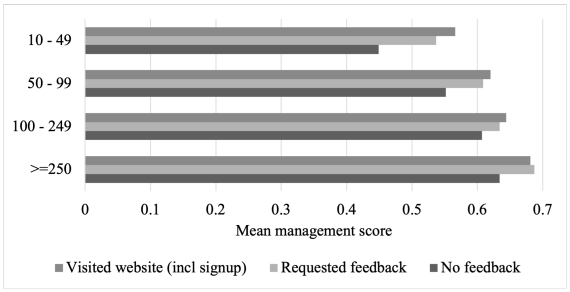
Second, in partnership with a publicly-funded business training organisation, Be The Business, we offered all sampled firms feedback on their relative performance, and for those that showed

[4]This finding complements earlier work on potential barriers to improvement in Bloom et al. (2012), World Bank Enterprise Surveys and Fischer and Karlan (2015), linking these to management practices and quality.

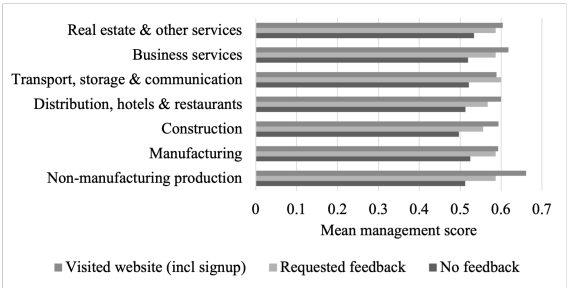
Figure 3: Mean management score at successive stages of the pipeline



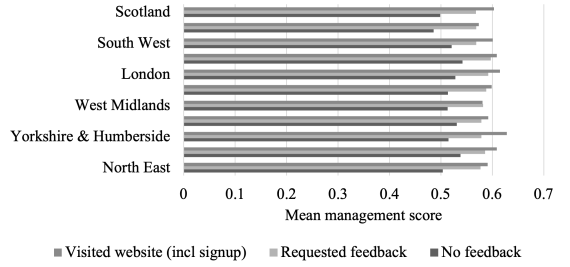
(a) Aggregate



(b) By size



(c) By industry



(d) By location

interest, the opportunity to participate in a free management mentoring programme. The mentoring programme ultimately failed due to low numbers; but we observe firms throughout the journey to sign-up, allowing us to understand *which* firms are interested in improving their management and the stage where firms lose interest.

We then designed a new module on the UK's new Business Insights and Conditions Survey (BICS). The BICS elicits qualitative information on firm expectations and beliefs. Prompted by the behaviour of firms in the mentoring scheme, we used the module to elicit firms' own *subjective beliefs* about their management practices and any barriers to improvement they face, as well as any actions they had taken to improve their management in the previous year. Finally, following early results from this project, we subsequently designed a custom module on MES2023 to test our hypotheses about firm awareness directly. Specifically, we asked firms to estimate their position in the management practices distribution within their industry, allowing us to compare subjective beliefs with objective performance.

Because we designed all three tools, we could link information across the three at the firm level to understand intentions, actions and outcomes jointly.[5]

[5]Both MES and BICS were administered by the UK Office for National Statistics (ONS).

To understand what actions firms take in between waves to improve their management practices, we link these data to the Annual Purchases Survey (APS) which collects firm-level expenditure on management consultancy services. The APS is part of the regular ONS business surveys and is sent to approximately 33,000 businesses annually. It aims to collect detailed information on business' expenditure on intermediate goods and services.

This paper makes three contributions: first, we harness the large longitudinal MES dataset of 9,683 firms responding to MES2016, 12,414 responding to MES2020 and 14,277 responding to MES2023 to provide new detail on who has improved their management practices, and who has not. We show that there is persistent dispersion in management practices that does not disappear over time, and also document strong correlations between management practices and desirable outcomes (such as higher productivity and survival). Together, these two facts replicate the puzzle we documented in the literature in the same same firm-level dataset. We show that neither learning nor differential survival are strong enough to narrow the dispersion of management practices over time.

Second, we examine the actions taken by 12,414 MES respondents to seek management improvements to understand the puzzle we uncovered. We show evidence of strong positive selection throughout the pipeline designed to channel firms to a free management mentoring programme. The better a firm's management practices, the further it goes to find out more about potential management improvements. Despite many of these actions being virtually costless, very few firms complete all steps necessary to receive the free mentoring. Firms that make it further into the pipeline also tend to have more managers relative to their workforce, and more educated managers. Firms also positively select into other forms of management improvement, such as whether to hire consultants. These actions are in turn positively and significantly related to subsequent management improvements supporting evidence in Ardanaz-Badia et al. (2022). By using an administrative mistake in the delivery of feedback in 2016, we are able to show that *intent* to improve matters for subsequent improvement, even absent any *informational treatment*. This is because intent leads to other actions to improve management, such as hiring consultants.

Finally, we use our linked MES-BICS data to understand the barriers firms face in improving their management. This allows us to understand *why* positive selection into management training occurs. The questions we designed for the BICS focus on barriers to improvement of management practices specifically.[6] We show that there are two distinct types of firms among those not seeking

[6]While the sample is only 10 % of the size of the full MES sample, the firms in the linked sample have very similar

management improvement. About 27 % of firms state that they lack time or money, or that changes would be too disruptive. These firms tend to be smaller and have a smaller share of managers, indicating that these managers lack the time or *capacity* to implement needed changes. A further 53 % of firms claim that they face "no barriers" but take no action to improve either. These are more likely to be firms with lower management scores, and more likely to be family-owned firms. Rather than facing capacity constraints, these are firms that lack the *awareness* of their need to improve. We validate the low-awareness hypothesis directly by designing a new question on MES2023 that explicitly asks firms to estimate their position in the management score distribution in their industry. Consistent with our other results, firms in the bottom 40% of the distribution are less likely to rank themselves correctly, and more likely to say that they face no barriers to improvement.

Our findings not only provide an explanation for the management puzzle we have noted earlier, but also have direct implications for business training programme design, evaluation and scale-up. First, they explain that depending on the *type* of firm policymakers are trying to reach information treatment (to overcome low awareness) or close support and subsidies (to overcome low capacity) may be necessary. Second, they indicate that findings on small pilots may not replicate across the larger population, *even if these pilot are correctly randomised controlled trials* (RCTs). As Sandvik et al. (2021) shows, these findings might be more widely applicable to workplace training programmes.

Our paper therefore contributes to five active strands of the literature. First, it complements the large and growing number of papers on the role of management in firm performance (Bloom et al., 2007; Bloom and Van Reenen, 2010; Bloom et al., 2014; Li et al., 2023) by documenting for the first time the positive selection into management improvement, and thus explaining the seeming puzzle. Second, it sheds new light on a hidden characteristic of a long tail of low-productivity firms, which a large literature has documented (Andrews et al., 2016; Adalet McGowan et al., 2018; Berlingieri et al., 2017). We contribute to this literature by providing new evidence on how willing they are to improve in one important dimension, management quality. We show at successive stages there is an unwillingness or inability to adopt more structured management practices which is a contributory factor behind laggard firm outcomes. Third, this paper speaks to the large number of studies, discussed earlier, that show that when information or training is accepted, take up is

characteristics.

low or temporary (Bruhn and Piza, 2022).[7] We show that take up is *selective* as well as low and temporary, and conditional on specific firm characteristics. Fourth, a large and growing literature studies low diffusion of best practices between frontier firms and others, and has identified it as a crucial source of static and dynamic inefficiency in developing and developed economies alike.[8] We contribute to this literature by identifying specific barriers to diffusion, rooted in firm capacity and awareness. Finally, this paper provides both better measures of the accumulation of management capital and knowledge transfer. While intangible capital more widely is an important contributor to positive firm outcomes (Crespi et al., 2007; Goodridge et al., 2016), management capital is perhaps the least well measured type of intangible capital (Black and Lynch, 2005; Ludewig and Sadowski, 2009; Squicciarini and Le Mouel, 2012).

This paper proceeds as follows. Section 2 describes the data sources. Section 3 discusses our results on the management puzzle, selection into management training and the types of barriers firms face. Section 4 discusses implications for programme design, evaluation and scale-up. A brief Section 5 concludes.

2 Data

We draw on four data sources: three UK business surveys, conducted by the ONS (the Management and Expectations Survey, the Annual Purchases Survey, and the Business Insights and Condition Survey) and visitor data from a custom-built website.

2.1 The Management and Expectations Survey

The MES collects information on the use of structured management practices across four categories: continuous improvement, or how businesses respond to problems; the use of key performance indicators (KPIs); the use of targets; and employment practices relating to promotion, training and employee underperformance. A first wave (MES2016) was dispatched as a paper questionnaire in the summer of 2017 and collected information about the 2016 reference year. A second wave (MES2020)

[7] In a design that complements ours, the authors undertake a study of 866 small and medium-sized Brazilian firms, providing different versions of an information sheet that compared management practices of similar firms and proposed five ways to improve these practices. Our paper differs from theirs in that we explore the take-up of management improvement options on offer rather than the use of information provided, but the conclusions are similar.

[8] In-class training for SMEs (Cole et al., 2009; Karlan and Valdivia, 2011) lead to improvements in business practices but less so business performance; subsidy of consultants makes large Indian textile firms aware of management practices (Bloom et al., 2013) and also improves practices for much smaller Mexican firms, (Bruhn et al., 2018) but not all firms could afford to take up consultancy even at subsidized rates.

was sent out as an electronic questionnaire in the autumn of 2020 and collected information for the 2019 and 2020 reference years. A third wave (MES2023) was dispatched in late 2023 for the 2023 reference year.

All three waves were sent to businesses in the market sector, excluding agriculture and finance, trading in Great Britain with 10 or more employees. The survey collected data on firms' management practices, expectations, business characteristics (such as ownership structure, input use and turnover), as well as wider organisational practices. MES2016 was sent to about 25,000 businesses, garnering roughly 8,000 responses (a response rate of 39%). MES2020 was sent to roughly 50,000 businesses, garnering 12,000 responses (a response rate of roughly 24%). MES2023 was sent to roughly 50,000 businesses, garnering 14,380 responses (a response rate of roughly 27%).

In MES2023, in addition to the core management practices questions, we designed a short module to investigate our hypotheses about firm awareness of management quality. Specifically, we asked firms to estimate which quintile of the management practices distribution within their industry their business occupied (Question 45: "In 2023, how do you think management practices in this business compare to those of other businesses in your industry?"). This allows us to directly compare firms' subjective assessments with their objective management scores.

In line with previous research (Bloom and Van Reenen, 2007), we calculate an overall management practices score for each firm by averaging scores from four categories described above. The overall management practices score is a continuous variable that falls between zero and one. A score of one indicates a firm has adopted the most structured management practices in all four areas; a score of zero denotes a firm that has failed to adopt even the most basic management practices.

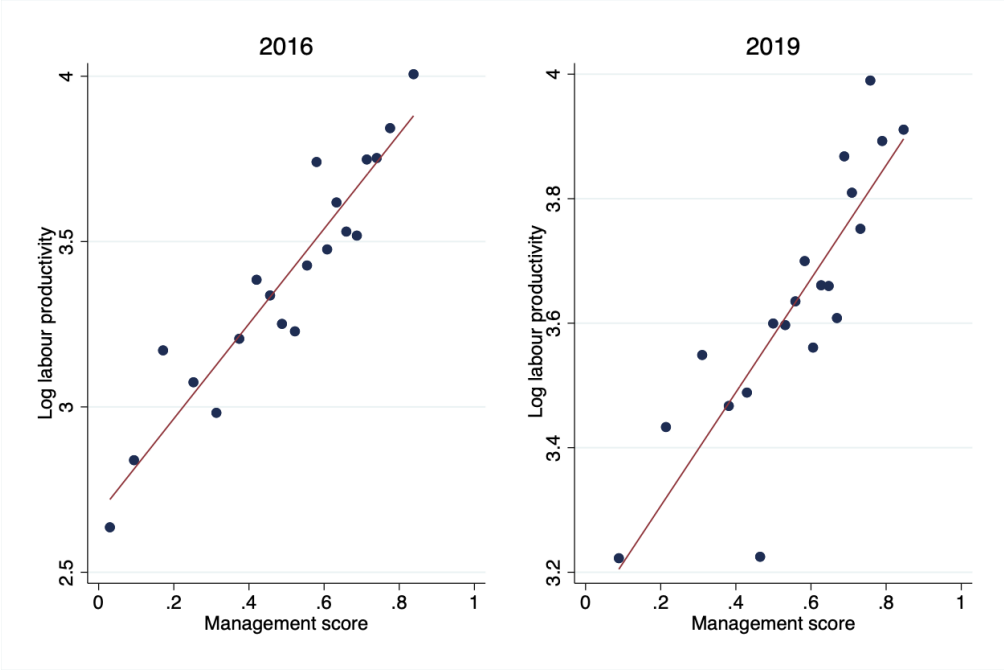
Our survey shows that management practices and firm productivity performance are positively correlated in the UK (see Figure 4). This correlation also holds when controlling for a wide range of firm characteristics (see Table A.3). Our results match findings from management surveys across the world (Bloom and Van Reenen, 2007).

2.2 The Annual Purchases Survey

The Annual Purchases Survey feeds into the UK National Accounts and among other variables collects firm-level expenditure on management consultancy services.[9] In a typical year, roughly

[9]The Annual Purchases Survey (APS) is part of the regular ONS business surveys and is sent to approximately 33,000 businesses annually. It aims to collect information about business' expenditure on energy, services, goods, and materials that are used up by the business activity, including raw materials, power and fuel, rental on buildings, and business services such as advertising and recruitment consultancy. It specifically excludes fixed assets or capital

Figure 4: Management practices and business performance in Great Britain (GVA per worker) are positively correlated



80% of surveyed firms, or 25,000 firms, answer the APS questionnaire. The linked MES2020-APS sample we use for analysis contains 2,775 firms.

Following Ardanaz-Badia et al. (2022), we use information on expenditure on consulting services as an indicator of firm motivation to improve which we hypothesise may drive management score changes. Because expenditure on consultancy services is not very frequent, we construct a dummy that takes the value one if a business spends any amount on consulting services in any available years between MES2016 and MES2020 (that is, in reference years 2016, 2017 or 2018), and zero otherwise.

2.3 The Business Insights and Conditions Survey

The Business Insights and Conditions Survey (BICS) is a fortnightly voluntary ONS business survey aiming to gather qualitative, rapid-response data on topical issues impacting UK businesses. Each wave of BICS is sent to approximately 50,000 businesses. A typical wave garners roughly 12,000 responses (a response rate of 24%). We were able to place two questions on management learning on BICS survey wave 64. The first question asked respondents what steps their business had taken over

investment, wages, and goods and services bought for resale without further processing. For further details, please see ONS (2019).

the last year to improve their management practices. The second asked respondents to name the largest barrier to management improvement their business faced over the last year. Both questions also provided a text box to capture answers not anticipated when designing the questions. When linking BICS wave 64 with MES2020, we obtain a linked sample of 1,237 firms. The Appendix contains more information about BICS wave 64.

2.4 Be The Business mentoring website data

From a carefully designed collaboration with a UK government funded mentoring scheme (*Be the Business*) we offered firms information on their own management practices score from MES2020, additional information about the importance of management practices and the offer of free mentoring. All respondents of MES2020 were offered the opportunity to receive additional feedback about their management practices across the different categories, compared to respondents in the same industry and region.[10] We tracked the visitor data to obtain information about which firms accessed the website, how much time they spent on different areas of the website and whether they decided to sign up to a free management mentoring programme; we then linked this to MES2020 using a key that translates the unique access code into a standard ONS reporting unit reference.

2.5 Summary Statistics

Table 1 presents the summary statistics for firms in the MES2016, MES2020 and the linked sample containing both. Overall there is evidence of little change in management score through time, since the level of the score was 0.57 in 2016 and 0.55 in 2020, which is well within one standard deviation and therefore not significantly different. This confirms our observation that management practices are fairly stable over time (see Figure 1). To test for sample selection bias, we also show the scores in the linked sample which give scores of 0.58 in 2016 and 0.57 in 2020. In the MES 2016 sample, the mean firm size is 242 employees, much higher than 139 in the MES 2020 sample. But the medians are closer, at 56 and 49 employees respectively.[11] The average firm age in 2016 sample is 16.60 years, while that in 2020 sample it is comparatively older at 19.10 years.

[10] Respondents were asked *Would you like to receive [Firm name]'s management practices score?*" (See Figure B.1), those who opted to receive feedback had a unique access code and the URL of a purpose-built, standalone website. The website provided visualisation of the management practices score of that particular business versus the distribution and mean of scores in the industry (See Figure B.2). A "Sign up for Free Mentoring" banner was added on that web page. When respondents clicked on that banner, they would see a description about the training program as well as an application form (See Figure **??**).

[11] The weighted means are also closer, at 60 and 49 employees respectively, as is shown in the Appendix Table A.1.

Table 1: Summary Statistics

	A. MES 2016			B. MES 2020			C. Linked sample		
	Mean	**SD**	**Count**	**Mean**	**SD**	**Count**	**Mean**	**SD**	**Count**
Management score 2016	0.57	0.21	9677	-	-	-	0.58	0.19	2694
Management score 2019	-	-	-	0.53	0.20	12413	0.56	0.19	2694
Management score 2020	-	-	-	0.55	0.20	12413	0.57	0.19	2694
Employment	242	971	9677	139	462	12413	196	504	2694
Family owned	0.57	0.50	9629	0.65	0.48	12413	0.61	0.49	2694
Foreign owned	0.11	0.31	9677	0.11	0.32	12413	0.14	0.34	2694
Share of managers in total workforce	0.17	0.16	9210	0.17	0.12	12168	0.16	0.10	2685
Share of managers with a college degree	0.38	0.35	9326	0.37	0.35	12412	0.39	0.34	2694
Age: 5 years or younger	0.08	0.27	9564	0.07	0.26	12413	0.01	0.10	2694
Age: 6-10 years	0.11	0.31	9564	0.12	0.32	12413	0.08	0.28	2694
Age: 11-15 years	0.11	0.31	9564	0.12	0.33	12413	0.11	0.31	2694
Age: 16-20 years	0.11	0.31	9564	0.13	0.33	12413	0.13	0.33	2694
Age: 21+	0.59	0.49	9564	0.56	0.50	12413	0.67	0.47	2694
Multiple sites	0.48	0.50	9677	0.42	0.49	12413	0.49	0.50	2694

3 Results

This section presents our main results. We first replicate the management puzzle in our microdata: we show that management practices are slow to change even though they are associated with significantly higher survival. We then use the linked MES and website data to document our main result: positive selection into management training. We then look at determinants of management improvement more widely, and document the importance of *intent*, even in the absence of an informational treatment, in driving management improvement. Finally, we present information on the barriers to improvement, which reveals two distinct categories of never-treated firms.

3.1 The Management Puzzle in the Microdata

There are two components to the management puzzle. First, we show that management practices change slowly over time, even at the firm level. Second, we show that they are associated with desirable outcomes, such as higher productivity and survival.

Table 2 shows the patterns of management change at the firm-level via a transition matrix for the three year period 2016-2019 and the one year period 2019-2020. We note two findings. First, despite the apparently static distributions illustrated in 1 there is movement between quintiles and this is not restricted to the firms in the upper quintiles. Therefore, management improvement is possible, even on relatively short timescales. Second, firms are still more likely to remain in their quintile of origin. This is especially true of the bottom and top quintiles. Therefore, convergence is incomplete and not enough to compress the overall distribution of management practices.

Figure 4 shows that management practices are positively and significantly associated with higher

Table 2: Transition matrix 2016 - 2019

		Management quintiles 2019					
		1	2	3	4	5	Total
Management quintiles 2016	1	46.64	25.11	15.70	5.38	7.17	100.00
	2	18.08	25.42	29.10	16.95	10.45	100.00
	3	7.85	17.71	26.96	29.38	18.11	100.00
	4	2.95	7.290	20.47	32.09	37.21	100.00
	5	1.24	3.22	10.15	24.13	61.26	100.00
	Total	9.34	12.15	19.23	24.54	34.74	100.00
		Management quintiles 2020					
		1	2	3	4	5	Total
Management quintiles 2019	1	82.65	12.21	2.23	1.92	0.99	100.00
	2	12.25	64.22	17.57	4.26	1.70	100.00
	3	2.12	17.86	57.22	18.23	4.57	100.00
	4	1.06	2.81	20.05	58.96	17.11	100.00
	5	0.45	0.90	2.11	17.37	79.17	100.00
	Total	13.40	15.75	19.57	23.32	27.96	100.00

Note: This table shows one-year and three-year transition matrices illustrating movement between quintiles of the management score quintiles calculated from weighted MES. Each cell shows the percentage of transitions. Transition probabilities are not weighted.

productivity. Table A.3 in the appendix shows that this relationship holds even when controlling for a large battery of controls.

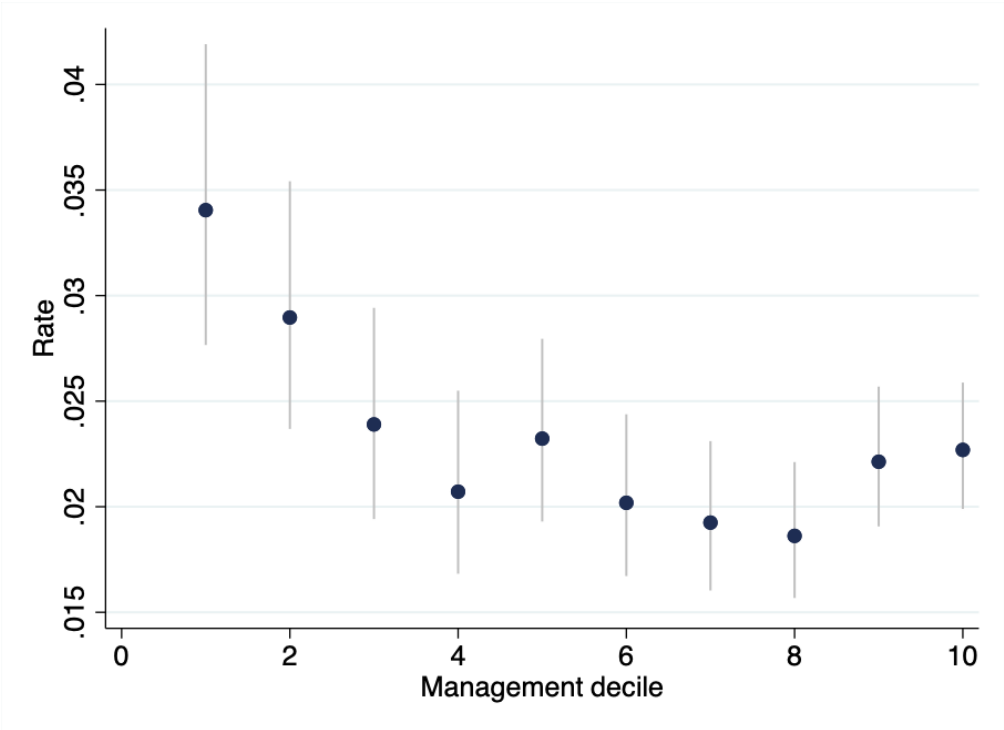
The rest of this section focuses on differential survival as the outcome of interest. Survival matters for two reasons. First, if better management increases a firm's odds of survival, this should itself provide a strong incentive to improve existing management practices. Second, if firms with worse management practices are less likely to survive, differential survival should itself decrease the dispersion of management practices.

We measure survival from the UK's business register, the Inter-Departmental Business Register (IDBR). The IDBR captures the universe of UK firms that have at least one employee paying Pay As You Earn (PAYE) employment taxes, or pay Value Added Tax (VAT).[12] We match MES 2016 with the IDBR from 2017 to 2020. We define a firm exiting the market when it is absent from the IDBR for one year and all the following years. To illustrate, if a firm appears in the IDBR for 2017 and 2018, but not for 2019 and 2020, it is considered as having exited in 2019 with a duration of three years. Therefore, the duration can range from one to five years. Out of the 9,683 firms in MES 2016, 995 exited the market by the end of 2020: of which 117 died in 2017, 301 died in 2018, 298 died in 2019, and 279 died in 2020. Appendix A.2 presents the descriptive statistics for failed firms and surviving firms separately.

[12]The cutoff for VAT in the UK is currently £90,000.

Figure 5 plots incidence rates, calculated as the number of failures relative to the total number of firms, on the vertical axis against management deciles on the horizontal axis. There is a negative correlation between incidence and management score for the first to sixth deciles, with the effect being most prominent for the first three deciles. Three of the four top deciles show no statistically significant difference in incidence compared with the sixth decile. This shows us that badly-managed firms have a higher incidence of failure.

Figure 5: Incidence rates by management deciles



To control for other observables, we follow previous research on firm survival and exits, and adopt a Cox proportional hazard model. The hazard function h(t) is specified as in Equation 1.

$$h(t) = h_0(t)(e)^{X\beta}, \tag{1}$$

where $h(t)$ is the rate at which firms exit at time t given that they have survived in $t-1$, h_0 is the baseline hazard function when all of the covariates equal zero, and X is a vector of firm characteristics.

The results of estimating the hazard model are presented in the Table 3. Column (1) presents the baseline model where only management score is included. The coefficient has a negative and significant coefficient, which means that firms with a higher management score have a lower like-

lihood of exiting. This negative relationship persists in column (2) although it is significant only at the 10% level due to the importance of industry, size, location and multiple sites among firm characteristics. Column (2) also allows for time fixed effects on the exit rate. Column (3) then introduces ownership and age into the equation, showing that foreign owned firms are more likely to exit but family owned and run firms are less likely to do so. The older the firm the less likely it is to exit. A higher share of managers with a college degree has a similar effect of reducing the likelihood of exit. Finally, column (4) add in the share of managers, which is insignificant, but otherwise the results are similar to before.[13] We conclude that the impact of management score on the likelihood of exiting is robust, negative and significant. While worse-managed firms are more likely to exit, the difference in survival rates is not enough to guarantee full convergence.

Table 3: Firm survival and management score

	(1)	(2)	(3)	(4)
Management score	-0.526***	-0.304*	-0.422**	-0.221
	-0.133	(0.156)	(0.169)	(0.182)
Family owned but not managed			-0.116	-0.145
			(0.103)	(0.108)
Family owned and managed			-0.199***	-0.198**
			(0.074)	(0.077)
Foreign owned			0.237**	0.207*
			(0.108)	(0.113)
Age: 6-10 years			-0.349***	-0.307***
			(0.109)	(0.116)
Age: 11-15 years			-0.756***	-0.708***
			(0.120)	(0.126)
Age: 16-20 years			-0.631***	-0.587***
			(0.118)	(0.125)
Age: 21+			-0.924***	-0.867***
			(0.095)	(0.101)
Share of manag degree			-0.212**	-0.181*
			(0.101)	(0.106)
Share of manag				-0.224
				(0.225)
Industry FE	No	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Location FE	No	Yes	Yes	Yes
Multiple sites	No	Yes	Yes	Yes
Observations	9677	9677	9171	8825
Log likelihood	-11144.362	-11036.335	-10002.701	-9208.645

Note: All estimates were obtained using a proportional hazard model. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[13] As a robustness check, we also used the complementary log–log (cloglog) model, which is considered more appropriate for discrete time survival analysis. The results are presented in Table A.4. The conclusions above still hold.

3.2 Selection into Management Improvement

This section discusses our main results: selection into the management training and other forms of management improvement are positively selected on firms' pre-existing management.

We estimate the determinants of a firm's desire to improve using cross-sectional OLS regressions. Our outcomes of interest are whether a firm asks for feedback, visits the website for more information and signs up for free mentoring. Outside our mentoring pipeline, we also verify that these results hold for the purchase of consultancy services, and for a self-reported battery of wider management improvements.

$$Y_i = \alpha + \beta M_i + \rho X_i + \sigma_i + \tau_i + \epsilon_i, \tag{2}$$

where Y_i is an indicator variable (binary variable) whether a firm requested feedback or not according to the MES, visited the website or not, observed spend on consulting services 2016-2018 from the ABS taking a similar approach to Ardanaz-Badia et al. (2022) or taken measures to make improvements or not according to the BICS. M_i indicates the recent management score of firm i, X_i are control variables of characteristics such as age, size, family owned and managed, not family owned, σ_i and τ_i denotes industry and regional fixed effects, and ϵ_i is a stochastic residual.

In Table 4 we report the results from OLS regressions of Equation (2) which reveal some stylised facts about who wants to improve using a wide range of sources (three surveys and a dedicated website). Columns (1) and (2) show the firms that request feedback, column (3) shows who visited the website to view the management score and receive information about it, column (4) shows who paid for consulting services 2016-2019 and column (5) shows who has taken wider actions according to the BICS survey. First, firms with higher management practices scores are more likely to want to improve. The coefficients on the management score 2019 are positive and significant. The magnitudes of the coefficients are particularly large for requesting feedback and taking actions, but they have positive coefficients for all other measures as well. Second, the type of firm affects the probability of wanting to improve. Family-owned firms and foreign firms are less likely to request feedback in 2020 or visit the website for more information. Family-owned and run firms were less likely to use consulting services 2016-19. Third, firms with a higher share of managers in the workforce or a higher share of managers with a degree were more likely to ask for feedback, visit the website for more information and sign up for free mentoring, or spend resources on consulting services. Therefore, a high pre-existing management score is the key predictor for firms' intention

to improve their management practices. A higher share of managers out of the total workforce, and better educated managers have additional explanatory power.

Table 4: Who wants to improve?

	(1)	(2)	(3)	(4)	(5)
	Requested feedback 2017	Requested feedback 2020	Visited website	Used consulting	Taken actions
Management score	0.555***	0.446***	0.158***	0.114**	0.738***
	(0.027)	(0.024)	(0.016)	(0.050)	(0.077)
Family owned but not managed	0.002	-0.034***	-0.024***	-0.033	-0.018
	(0.018)	(0.013)	(0.009)	(0.026)	(0.036)
Family owned and managed	0.010	0.013	-0.003	-0.041**	-0.015
	(0.013)	(0.012)	(0.008)	(0.021)	(0.033)
Foreign owned	-0.020	-0.039**	-0.039***	0.018	-0.048
	(0.019)	(0.016)	(0.010)	(0.025)	(0.037)
Age: 6-10 years	-0.035	0.008	-0.006	-0.012	-0.089
	(0.024)	(0.021)	(0.014)	(0.043)	(0.072)
Age: 11-15 years	-0.025	-0.002	0.004	-0.002	0.044
	(0.024)	(0.021)	(0.014)	(0.042)	(0.066)
Age: 16-20 years	-0.029	0.009	0.003	-0.034	-0.062
	(0.024)	(0.021)	(0.015)	(0.042)	(0.068)
Age: 21+	0.012	0.039**	0.009	-0.050	-0.017
	(0.020)	(0.019)	(0.013)	(0.036)	(0.060)
Share of manag	0.085**	0.103***	0.054**	0.168**	0.061
	(0.039)	(0.038)	(0.025)	(0.070)	(0.159)
Share of manag degree	0.022	0.082***	0.058***	0.061**	0.032
	(0.017)	(0.015)	(0.010)	(0.029)	(0.049)
Industry FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Multiple sites	Yes	Yes	Yes	Yes	Yes
Observations	8574	12134	12134	3222	1522
R2	0.065	0.052	0.028	0.140	0.131

Notes: Control variables for Columns (1) and (4) are in year 2016. Control variables for columns (2), (3), and (5) are in year 2019. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.3 Determinants of Within-firm Changes to Management Practices

We look next at the factors that are correlated with within-firm changes to management practices from 2016 to 2019 to test the hypothesis that firms that requested feedback or used consulting services in previous years had greater improvement in management. In particular, we estimate

Table 5: Who has improved? Score change 2016 - 2019

	(1)	(2)	(3)	(4)	(5)
Management score	-0.486***	-0.491***	-0.524***	-0.524***	-0.537***
	(0.021)	(0.021)	(0.038)	(0.038)	(0.039)
Family owned but not managed	0.007	0.005	0.018	0.018	0.022*
	(0.010)	(0.010)	(0.013)	(0.013)	(0.013)
Family owned and managed	-0.005	-0.006	-0.006	-0.006	-0.003
	(0.007)	(0.007)	(0.012)	(0.012)	(0.012)
Foreign owned	0.013	0.012	0.013	0.015	0.017
	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)
Age: 6-10 years	0.008	0.008	-0.008	-0.009	-0.009
	(0.018)	(0.018)	(0.038)	(0.038)	(0.037)
Age: 11-15 years	-0.001	-0.002	-0.021	-0.021	-0.019
	(0.018)	(0.018)	(0.035)	(0.035)	(0.034)
Age: 16-20 years	-0.030*	-0.032*	-0.042	-0.042	-0.043
	(0.018)	(0.018)	(0.038)	(0.038)	(0.037)
Age: 21+	-0.033**	-0.035**	-0.019	-0.020	-0.022
	(0.016)	(0.016)	(0.034)	(0.034)	(0.033)
Share of manag	0.060**	0.059**	0.112**	0.118**	0.113**
	(0.029)	(0.029)	(0.049)	(0.049)	(0.049)
Share of manag degree	0.022**	0.021**	0.030*	0.031*	0.033*
	(0.010)	(0.010)	(0.017)	(0.017)	(0.017)
Requested feedback		0.015***	0.004	0.004	
		(0.006)	(0.010)	(0.010)	
Using consulting in 2016 - 2018			0.018*		0.014
			(0.010)		(0.010)
Industry FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Multiple sites	Yes	Yes	Yes	Yes	Yes
Observations	2551	2487	925	925	950
R2	0.280	0.282	0.343	0.341	0.344

Note: The dependent variable is the management score change from 2016 to 2019. Control variables are in year 2016. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Equation 3.

$$M_{i,t} - M_{i,t-1} = \alpha + \beta Request_{i,t-1} + \gamma M_{i,t-1} + \rho X_{i,t-1} + \sigma_i + \tau_i + \epsilon_{i,t}, \tag{3}$$

where $M_{i,t}$ indicates the management score of firm i in year t, $Request_{i,t-1}$ is a dummy that equals to one if firm i has requested to receive feedback in year $t-1$, $X_{i,t-1}$ are firm-specific and time-varying control variables, σ_i and τ_i denotes industry and regional fixed effects, and $\epsilon_{i,t}$ is a stochastic residual.

In Table 5, we document the types of firms that have improved their management practice from 2016 to 2019. In column (1), we regress the management score change from 2016 to 2019 on

Table 6: Who has improved? Score change 2019 - 2020

	(1)	(2)	(3)	(4)
Management score	-0.107***	-0.112***	-0.112***	-0.109***
	(0.005)	(0.005)	(0.005)	(0.005)
Family owned but not managed	-0.001	-0.000	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Family owned and managed	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Foreign owned	0.005*	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Age: 6-10 years	-0.009**	-0.009**	-0.009**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Age: 11-15 years	-0.008*	-0.008*	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Age: 16-20 years	-0.017***	-0.017***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
Age: 21+	-0.016***	-0.017***	-0.017***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Share of manag	0.001	0.000	0.000	0.001
	(0.008)	(0.008)	(0.008)	(0.008)
Share of manag degree	0.008***	0.007***	0.007***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Requested feedback		0.011***	0.010***	
		(0.002)	(0.002)	
Visited website			0.004	0.010***
			(0.003)	(0.002)
Industry FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Multiple sites	Yes	Yes	Yes	Yes
Observations	12167	12134	12134	12134
R2	0.093	0.096	0.096	0.094

Note: The dependent variable is the management score change from 2019 to 2020. Control variables are in year 2019. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

overall management score in 2016, with industry and location fixed effects. This shows that there is substantial mean reversion in management scores, but as we add further regressors in later columns we see who has improved their management score. In column (2), we include an indicator variable which equals one if the firm has requested to receive feedback about their management in MES 2016 and zero otherwise. This variable reflects a firm's motivation to know more about management and make improvements. The statistically significant positive coefficient shows the intention to improve has an impact on actual change in management practices over a three year period, accounting for an increase of 7.5% of the standard deviation of the average score in 2019.

Due to a clerical error, firms that requested feedback in 2017 never actually received any. There-

fore, any positive effect on subsequent management practices estimated here is due to the *intent* to improve rather than any *information* trough feedback received. In other words, it is a selection effect rather than a treatment effect. In column (3) we register whether a firm paid for consulting services in the period 2016-18 (after the data collected by MES2016 but prior to MES2020). This measures actual actions taken over the period 2016 to 2019 to improve management practices. We find that this has a positive effect on the score, which is slightly larger increase of 9% of the standard deviation of the average score in 2019. Moreover, once we include this proxy of actions taken, the coefficient on intent becomes insignificant. This suggests that intent affects subsequent management practices precisely because it leads firms to take improvement actions.

In columns (1-5) we control for firm characteristics (including the logarithm of employment), family ownership and foreign ownership and age. We find that larger firms are significantly more likely to improve their management score, but not those firms that are family owned and run. Age has a negative and significant effect, suggesting that all else equal older firms do not improve their management scores. We also include in all specifications the share of managers in the workforce and the share of managers holding a college degree qualification. This allows for the quantity and quality of management, and both contribute positively to the management score change, over and above the size, age or ownership structure of the firm.

In Table 6 we repeat the earlier exercise to explore the determinants of the change in management score for a shorter window between 2019 and 2020 using MES 2020. The value of reviewing this table is that this period covers the onset of Covid-19. Coefficients for the management score variable are the same sign but smaller in magnitude (adjusting for the one-year window length here compared with three-year length in Table 5). Firm characteristics have some similarities, since firm age is associated with a lower score change and foreign-owned firms have a higher score, which is significantly different from zero in 6. The share of managers is not significant but the share of managers with a college degree has a positive coefficient indicating a similar influence that raises management score. The effect of requesting feedback remain statistically significant and positive, as does visiting the website when included individually. We conclude that despite challenging conditions under Covid-19 the relationships with our explanatory variables are robust: better-managed firms and those that are larger, younger, with more qualified managers tended to improve their management scores. Requesting feedback signals reliably intent to improve, even when no feedback is delivered.

Table 7: Who has improved? Continued

	(1) Full sample	(2) Full sample	(3) Linked sample	(4) Linked sample	(5) Full sample	(6) Linked sample
	2020 - 2023	2020 - 2023	2020 - 2023	2016 - 2019	Two periods	Two periods
Management score	-0.487***	-0.492***	-0.522***	-0.446***	-0.492***	-0.491***
	(0.014)	(0.014)	(0.030)	(0.030)	(0.012)	(0.020)
Requested feedback		0.009**	0.024***	0.016*	0.013**	0.017**
		(0.004)	(0.008)	(0.008)	(0.006)	(0.008)
Survey year = 2020					0.040***	0.043***
					(0.006)	(0.010)
Requested feedback × Survey year = 2020					-0.003	-0.001
					(0.007)	(0.011)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Multiple sites	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4843	4834	1118	1118	7320	2317
R2	0.292	0.293	0.375	0.317	0.296	0.335

Notes: In columns (1) - (2), the dependent variable is the management score change from 2019 to 2020; the sample contains firms that responded to both MES2020 and MES2023. In columns (3) - (4), the dependent variable is the management score change from 2023 to 2023, and from 2019 to 2020, respectively. The sample contains firms that responded to MES2016, MES2020 and MES2023, to facilitate calculations of score changes across three waves. In columns (5) and (6), samples from MES 2016 to 2019 and those from MES 2019 to 2023 are stacked; a survey year dummy is used to differentiate the two time periods. Column (5) uses the full sample, whereas column (6) uses the repeated sample in both periods. Control variables use the level at base year. For example, for score change 2020 to 2023, control variables would be the levels of 2020. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Finally, Table 7 compares changes over the three-year period 2016-19 (when firms could request feedback but did not receive it) with changes over the three-year period 2020-23 (when firms who requested feedback actually received it). This allows us to understand the differential *information* effect of feedback, on top of any selection on *intent*. Columns (3) and (4) show that the effect of receiving feedback is 50% larger in the three years following the 2020 wave compared to the the 2016 wave (suggesting a sizeable information effect). However, pooled and panel regressions that specifically allow us to test for a differential effect following the 2020 wave in columns (5) and (6) suggest that this difference is merely compositional. Improvement from selecting into treatment comes from selection on the firms' *intent*, not the information treatment they receive.

3.4 Barriers to Management Improvement

Firms may not adopt better management practices for a variety of reasons. There has been evidence in Bloom et al. (2012), Fischer and Karlan (2015), and World Bank Enterprise Survey (WBES) that among other explanations, human resource management, financial, sales and marketing and government may be *external* barriers to growth and better performance. But firms also face quite specific *capacity* constraints that leave them lacking time and resources to learn about ways to improve the quality of their management practices. Additionally, firms may lack the *awareness* that their management practices need improvement. The previous section indicates that these latter types of barriers may be quite important but have not previously been explored in depth. Therefore, we introduce targeted questions to the BICS survey to shed light on this issue.

We measure *capacity* constraints in two ways: first, indirectly, by looking at the correlates of non-response among firms we know to still be active; and secondly, directly, in the self-declared questions on barriers. We measure *awareness* as those firms that declare that they do not face any barriers to management improvement, but nonetheless take no actions to improve.

We first explore non-response, and find that firms with lower management scores are significantly less likely to respond to the survey. According to columns (1 - 2) of Table 8, decreasing the management practices score of a firm by 0.1 percent (roughly equivalent to moving a firm from the upper quartile to the median) decreases the likelihood of response by three percentage points, or roughly 12% of the average response rate of 25%. This non-response effect is highly statistically significant and stable across specifications that allow for requested feedback or not. Additionally, the act of requesting feedback is also negatively and statistically significantly associated with non-response. This is consistent with our theory that firms that request feedback signal that they both

Table 8: Barriers to Management Learning

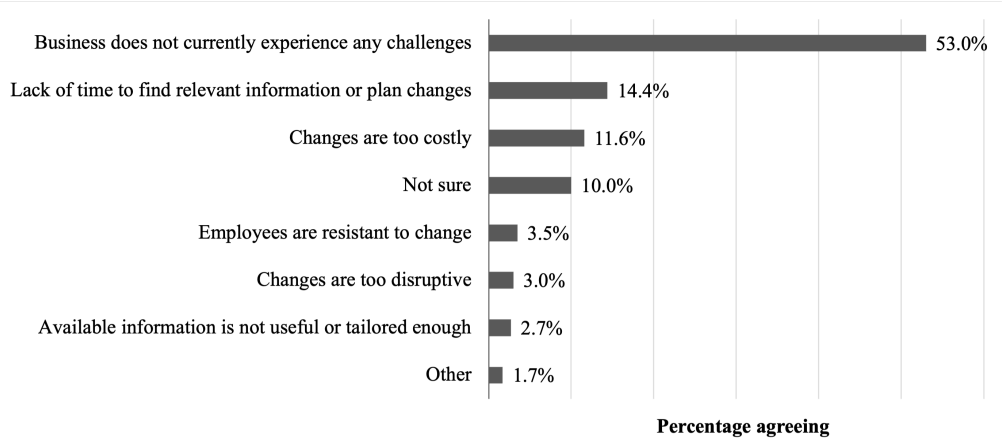
	(1)	(2)
Management score	-0.308***	-0.278***
	-(0.069)	(0.070)
Family owned but not managed	-0.021	-0.019
	-(0.03)	(0.030)
Family owned and managed	-0.034	-0.031
	-(0.028)	(0.028)
Foreign owned	0.016	0.016
	-(0.031)	(0.031)
Age: 6-10 years	-0.005	-0.012
	-(0.058)	(0.058)
Age: 11-15 years	-0.014	-0.021
	-(0.055)	(0.056)
Age: 16-20 years	-0.023	-0.027
	-(0.055)	(0.055)
Age: 21+	-0.029	-0.035
	-(0.049)	(0.049)
Share of manag	0.254**	0.265**
	-(0.128)	(0.128)
Share of manag degree	0.031	0.033
	-(0.04)	(0.040)
Requested feedback	-0.060***	-0.095***
	(0.021)	(0.028)
Industry FE	Yes	Yes
Size FE	Yes	Yes
Location FE	Yes	Yes
Multiple sites	Yes	Yes
Observations	1527	1520
R2	0.073	0.078

Note: For columns (1) and(2), the dependent variable is a dummy variable which equals one if a firm responded to BICS wave 64 but did not answer the barrier question, and zero otherwise. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

understand the need to improve and have the capacity to do so.

Among the 6,702 firms who responded to BICS64 we show that at 53%, the most common response in Figure 6 is that the firm is currently not experiencing any challenges to management improvement. This is indicative of low awareness. The second most common response, at a total of 29%, is lack of time (14.4%), money (11.6%) or the fear that the process of change would be too disruptive (3%). These responses, just like non-response, are indicative of the firm facing capacity or time constraints that prevent management improvement. Crucially, both non-responders and firms reporting no challenge are overrepresented at the bottom of the management practices score distribution, relative to other firms (see Figure A.2).

Figure 6: The main challenge for improving management practices according to BICS64 (weighted)



3.5 Direct evidence of low awareness

The previous section documented two types of firms among non-improvers: those reporting capacity constraints and those reporting "no barriers." We hypothesised that the latter group suffers from low awareness: that is, they do not recognise their own management gaps. Informed by our early results, in MES2023, we were able to test this hypothesis directly. In addition to questions about firms' objective management practices, we asked respondents to estimate in which quintile of the management practices distribution of their industry their firm would sit.

Table 9 compares firms' subjective assessments with their actual performance. As documented in other studies, for example, by Kruger and Dunning (1999); Malmendier and Tate (2015); Huffman et al. (2022), managers are generally overconfident, believing their management practices to be relatively better than they are in practice (see Figure A.1). The diagonal of Table 9 shows the share of firms that correctly identified their quintile—ranging from only 5.14% in the bottom quintile to 14.27% in the top quintile. Most notably for our purpose, firms in the bottom two quintiles were least likely to correctly estimate their own rank. Instead, nearly 90% of bottom-quintile firms believed they were average or better, with only 11.58% recognizing they were below average. This provides direct evidence of low awareness among the firms with the lowest management practices scores.

Table A.5 shows that correctly predicting one's management practices quintile is positively and significantly associated with a firm's management practices score, and negatively and significantly associated with the probability of reporting no challenge, even controlling for industry, size, location and other firm characteristics. In other words, better-managed firms are more likely to correctly

predict their performance, and less likely to say they do not need to improve, than their worse-managed peers. This establishes that the link between low management quality and low awareness is not merely a compositional artifact but holds for otherwise identical firms.

Table 9: Distribution of manager predictions about own management and comparison to realisations

		Actual management quintiles					
		1	2	3	4	5	Total
Subjective management quintiles	1	5.14	1.28	0.82	0.47	0.32	1.34
	2	6.44	5.72	3.55	2.41	1.15	3.52
	3	59.9	57.22	54.52	47.84	36.36	49.92
	4	20.49	28.27	33.32	39.04	47.9	35.33
	5	8.03	7.52	7.78	10.24	14.27	9.89
	Total	100	100	100	100	100	100

Note: This table compares firm's subjective prediction about their management in Question 45 of MES, "In 2023, how do you think management practices in this business compare to those of other businesses in your industry?", against the actual performance. 1 represents the bottom 20 percent whereas 5 represents the top 20 percent. Each cell shows the percentage of firms, with the column total being 100.

4 Policy Implications: Firm Types and Programme Design

4.1 Firm Types

This paper has established new findings about selection into management training, and the barriers that stop firms from improving. Appendix C develops a simple model (of a firm i with current management quality m_i that chooses effort e_i to improve) that rationalises our findings. Crucially, heterogeneity in both capacity and awareness is needed to reconcile all our results.

In the model, θ_i represents the firm's ability to process information and implement changes. This captures both the quantity and quality of managerial resources, or "bandwidth" available for improvement activities. In contrast to the large and influential literature on barriers to adoption pioneered by Parente and Prescott (1994), we focus on barriers internal to the firm. By contrast, α_i represents the firm's perception of its management quality gap. This focus on awareness is related to a growing literature on behavioural inattention and its effects on optimal decisions.[14]

The model then delivers three key insights. First, positive selection arises from complementarity. The cross-partials $g_{e\theta} > 0$ and $c_{e\theta} < 0$ create complementarity between firm characteristics (m_i, θ_i, α_i) and improvement effort. This generates positive selection even though poorly-managed

[14]For a comprehensive survey, see Gabaix (2019).

firms have higher marginal returns ($f''(m) < 0$). In a dynamic version of the model, the positive correlation between existing management practices on the one hand and capacity (θ_i) and awareness (α_i) on the other arises endogenously. Second, two dimensions of heterogeneity are needed to rationalise our findings. Separating awareness α_i (recognition of gaps) from capacity θ_i (resources to act) is essential. Conflating these leads to incorrect policy prescriptions. Third, three firm types emerge naturally. The joint distribution of (θ_i, α_i) generates three firm types with distinct behaviors and policy needs: high-capacity firms (high θ, high α) that respond to market incentives; low *awareness* firms (high θ, low α) that need information interventions; and low *capacity* firms (low θ, high α) that need implementation support. These predictions organise our empirical findings and provide a precise, empirically testable framework for policy design.

4.2 Programme Design

Our findings have important implications for the design of business support programmes. Positive selection affects the design, evaluation and scale-up of business training programmes. In addition, one-size-fits-all interventions fail because different firms face fundamentally different barriers. We discuss targeted approaches for each firm type, drawing on emerging evidence from the training programmes literature.

Our findings contribute to a growing literature on business training programmes, much of which focuses on RCTs in developing countries. McKenzie (2021) and Bruhn and Piza (2022) review evidence from dozens of studies, concluding that training impacts are often modest and temporary. However, these studies typically cannot separate selection effects from treatment effects because they only observe firms *after* they have opted into programmes. Our contribution is documenting the *selection process itself*. By measuring management practices before firms are offered improvement opportunities, we show that positive selection explains low aggregate take-up and potentially biases treatment effect estimates. Studies that randomise among voluntary applicants (Bloom et al., 2013) capture treatment effects on selected firms (those with high capacity and awareness) but miss potential gains from reaching non-participants.

The "leaky pipeline" documented in Section 3 illustrates why untargeted programmes achieve low take-up. Offering the same intervention to all firms yields strong positive selection: those with least to gain participate, while those with most to gain do not. This pattern appears across many settings, including the earlier cited Innovation Growth Lab RCT (43 of 500 firms completed), the UK Help to Grow programme (less than 10% of target enrolled), and numerous studies reviewed in

Bruhn and Piza (2022) and McKenzie (2021).

Recent evidence from Sandvik et al. (2021) suggests this mechanism is not solely limited to business training programmes. In a field experiment comparing voluntary versus mandatory workplace mentorship, they find the best employees opt into voluntary programmes but have the smallest treatment effects. Making participation mandatory substantially increases aggregate gains precisely because it includes those who benefit most but would not voluntarily participate. Our firm-level findings parallel theirs: the worst-managed firms—who would benefit most from mentoring—are least likely to engage with improvement opportunities. This does not mean all business support programmes should be mandatory. Rather, it suggests that programme design must explicitly address the selection problem by understanding *why* different firms fail to participate and tailoring interventions accordingly.

Our typology suggests different policy approaches for different firms. Low-awareness firms lack recognition of management gaps. A recent study by Phipps and Fuller (2022) at the UK Innovation Growth Lab speculates that lack of information and awareness are key barriers to firm learning, but that persuasion can lead progressively to a decision to adopt and implement, which in turn makes firms more likely to be open to other improvements.[15] These firms need information and benchmarking interventions to build awareness. This might include simple, salient comparisons to peer firms, low-cost diagnostic tools that make gaps visible and nudges to highlight the link between management and performance. Adem et al. (2023) provides a successful example: offering businesses website performance data relative to peer groups and benchmarks led to improved website performance within a month. The key was making information salient and actionable. Sandvik et al. (2020) suggests another path in the context of workplace training programmes. They find that structured opportunities for peer learning substantially improve sales performance, with the largest gains for those matched with high-performers. In other words, low-awareness workers do not know what they do not know until given exposure to better practices. This suggests that for low-awareness firms, peer-to-peer exposure might be more effective than formal training.[16]

By contrast, the primary barrier for low-capacity firms is insufficient managerial resources and time. Consistent with our evidence, Burchell and Wallis (2021) found zero take-up when the ap-

[15] Wu and Broughton (2019) from the UK Behavioural Insights Team echoes this conclusion in reviewing a wider set of interventions and notes that low adoption of proven management practices and technology are often linked to mistaken assessment of costs or benefits, over-weighting of risks (loss aversion), a poor mentality towards growth or improvement, or overconfidence.

[16] Delfino et al. (2026) provides similar evidence of low awareness as a barrier to training in a worker context. Low-cost informational interventions prove successful at encouraging workers to take up reskilling offers.

plication process was too complex relative to perceived benefits. These firms therefore need active support and simplified implementation. Some successful examples of past training programmes offer a path forward. Anderson and McKenzie (2022) found that market-provided support (outsourcing expertise) was more impactful than training and more cost-effective than consulting for SMEs. Bruhn and Piza (2022) showed that simplifying the first steps towards adoption significantly increased take-up. Several World Bank-sponsored studies of external interventions have proven effective in developing countries (Bruhn et al., 2018; Apedo-Amah et al., 2020), but studies in advanced economies find similar results (Adams et al., 2016). Visits from mentors show mixed results. Brooks et al. (2018) followed mentoring relationships with entrepreneurs in Kenya, where the mentoring improved performance initially but the improvement disappeared after the relationship ended, while Dalton et al. (2021) show that best practices information supplemented by a visit to apply the information yields greater improvement. This once again suggests that low-capacity firms benefit from more intensive support when delivering business improvement programmes.

Finally, a corollary of our findings in Section 3 is that natural selection is generally insufficient for convergence in management practices. First, even bottom-decile firms have three-year survival rates of around 85% (Figure 5). At this pace, it would take decades for natural selection to substantially shift the distribution. Second, government policies often work against selection, whether through bailouts, loan guarantees, or evergreening. In the meantime, poorly-managed firms impose externalities: they hold onto resources like capital and labour that could be deployed more productively elsewhere (McGowan et al., 2017). This suggests that there is indeed an important role for active policy programmes to accelerate management improvements.

Our paper has implications beyond management training. In an agricultural setting, Hanna et al. (2014) show that Indian farmers do not adopt profitable technologies even when subsidised and find that directing farmer's awareness to neglected dimensions can help. Our framework suggests that distinguishing farmers who do not recognise the benefit (low awareness) from those who cannot afford adoption costs or implementation time (low capacity) may yield even greater payoffs. Sandvik et al. (2021) show that employee mentoring, when voluntary, also leads to positive selection, and therefore lower-than-optimal returns. Our paper suggests an alternative to mandatory employee training programme: tailoring programmes to remove the barriers, whether awareness or capacity, keeping employees from taking up profitable training opportunities.

5 Conclusions

We started by documenting a puzzle: A growing literature finds evidence that good management practices are associated with better productivity, survival and innovation outcomes (Bloom et al., 2007; Bloom and Van Reenen, 2010; Bloom et al., 2014, 2021), with much of this effect seemingly causal (Bloom et al., 2013; Giorcelli, 2019). Yet while some firms improve rapidly, wide dispersion of management scores remains, and take-up even of free support programmes is abysmally low.

In this paper, we use three novel, purpose-built data sources to explain this puzzle. We track firms' management practices over time, their progress through the pipeline to our own management mentoring programme with a respected UK provider, and their intentions, beliefs and actions to improve their management. While the mentoring programme failed due to low take-up, it yielded unique and novel data on the endogenous selection into management training.

In addition to replicating the management puzzle at the firm level, we document for the first time that take-up is not just low, but strongly positively selected. Firms that stand most to benefit from the training programme are least likely to sign up for it. We show that this selection pattern holds for other actions likely to lead to management improvement too. We show that firms taking actions that signal a willingness to improve see their management practices score rise in later waves. In a twist of fate, a clerical error prevented firms that requested feedback in 2016 from ever receiving our feedback. They subsequently improved too, suggesting that a firm's *intention* to improve matters quite apart from any information treatment. Using a custom-designed survey module, we uncover two distinct barriers to management improvement: low *awareness* of the need to improve, and time or *capacity* constraints. These types are correlated with observable features of the firm, such as its size, ownership structure and the number and educational background of its managers.

Our paper provides new insights into why management training programmes, and business training programmes more widely, often fail at the implementation, evaluation or scale-up phase. One-size-fits-all programmes are likely to attract only the best-managed firms. Targeted information campaigns and administrative and financial support are needed to attract low-awareness and low-capacity firms, respectively, who have the most to gain. This also means that even successfully randomised RCTs may subsequently fail to scale up, because the initially attracted study population is positively selected compared to the universe of firms. To correct for this bias, researchers and policymakers may want to survey a random sample of the population of interest *before* allowing subjects to express interest in their programme.

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A Figures and tables

Table A.1: Summary Statistics (weighted)

	A. MES 2016		**B. MES 2020**		**C. MES 2023**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Management score (survey year)	0.49	0.23	0.49	0.21	0.56	0.19
Management score (previous year - 2019)	-	-	0.48	0.21	-	-
Employment	60	396	49	236	51.2	432.44
Family owned	0.67	0.47	0.73	0.45	0.71	0.46
Foreign owned	0.04	0.2	0.06	0.24	0.06	0.24
Share of managers in total workforce	0.19	0.16	0.19	0.14	0.19	0.12
Share of managers with a college degree	0.34	0.38	0.36	0.38	0.38	0.38
Age: 5 years or younger	0.13	0.34	0.13	0.33	0.11	0.31
Age: 6-10 years	0.16	0.36	0.15	0.35	0.15	0.36
Age: 11-15 years	0.15	0.35	0.15	0.36	0.14	0.35
Age: 16-20 years	0.12	0.32	0.14	0.35	0.12	0.33
Age: 21+	0.45	0.50	0.43	0.50	0.47	0.5
Multiple sites	0.30	0.46	0.28	0.45	0.31	0.46

Table A.2: Summary statistics for survived and failed firms

	Survived firms			Failed firms		
	Mean	**SD**	**Count**	**Mean**	**SD**	**Count**
Management score	0.58	0.20	7799	0.56	0.21	1035
Employment	211	589	7799	237	1343	1035
Family owned	0.57	0.49	7799	0.57	0.50	1035
Foreign owned	0.11	0.31	7799	0.11	0.32	1035
Share of managers in total workforce	0.17	0.14	7799	0.17	0.15	1035
Share of managers with a college degree	0.39	0.35	7799	0.38	0.36	1035
Age: 5 years or younger	0.07	0.25	7799	0.14	0.35	1035
Age: 6-10 years	0.1	0.3	7799	0.15	0.36	1035
Age: 11-15 years	0.11	0.32	7799	0.11	0.32	1035
Age: 16-20 years	0.11	0.31	7799	0.12	0.32	1035
Age: 21+	0.61	0.49	7799	0.47	0.5	1035
Multiple sites	0.48	0.5	7799	0.48	0.5	1035

Table A.3: Labour productivity and management score

	MES 2016			MES 2019		
	(1)	(2)	(3)	(4)	(5)	(6)
Management score	0.918***	1.036***	0.824***	0.749***	0.777***	0.609***
	(0.065)	(0.070)	(0.072)	(0.064)	(0.063)	(0.065)
Family owned but not managed			-0.076**			-0.035
			(0.036)			(0.031)
Family owned and managed			-0.113***			-0.051*
			(0.026)			(0.027)
Foreign owned			0.264***			0.252***
			(0.036)			(0.036)
Age: 6-10 years			0.293***			0.113
			(0.068)			(0.076)
Age: 11-15 years			0.378***			0.222***
			(0.065)			(0.073)
Age: 16-20 years			0.395***			0.240***
			(0.064)			(0.072)
Age: 21+			0.412***			0.244***
			(0.059)			(0.068)
Share of manag			0.095			0.429**
			(0.187)			(0.174)
Share of manag degree			0.255***			0.194***
			(0.039)			(0.039)
Industry FE	No	Yes	Yes	No	Yes	Yes
Size FE	No	Yes	Yes	No	Yes	Yes
Location FE	No	Yes	Yes	No	Yes	Yes
Multiple sites	No	Yes	Yes	No	Yes	Yes
Observations	7914	7914	7287	6713	6713	6667
R2	0.029	0.290	0.316	0.021	0.244	0.265

Notes: The dependent variable is the logorithm of GVA per worker in 2016 and 2019 as indicated at the top of the table. Control variables are in year 2016 for columns (1) - (3) and in year 2019 for columns (4) - (6). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Firm survival and management: complementary log–log model

	(1)	(2)	(3)	(4)
Management score	-0.538***	-0.308**	-0.428**	-0.218
	(0.133)	(0.157)	(0.169)	(0.182)
Family owned but not managed			-0.120	-0.150
			(0.103)	(0.108)
Family owned and managed			-0.200***	-0.199***
			(0.074)	(0.077)
Foreign owned			0.240**	0.209*
			(0.108)	(0.113)
Age: 6-10 years			-0.359***	-0.315***
			(0.109)	(0.116)
Age: 11-15 years			-0.772***	-0.722***
			(0.120)	(0.126)
Age: 16-20 years			-0.645***	-0.599***
			(0.118)	(0.125)
Age: 21+			-0.946***	-0.886***
			(0.095)	(0.101)
Share of manag degree			-0.220**	-0.187*
			(0.101)	(0.106)
Share of manag				-0.236
				(0.225)
Industry FE	No	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Location FE	No	Yes	Yes	Yes
Multiple sites	No	Yes	Yes	Yes
Observations	54645	54645	51914	50106
Log likelihood	-5844.360	-5730.777	-5236.634	-4887.613

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Firms are overconfident about their management

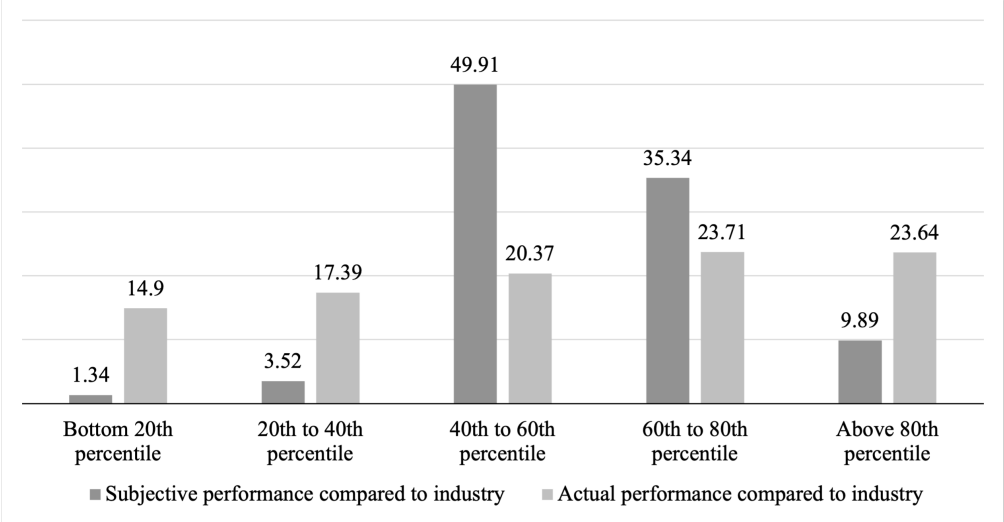
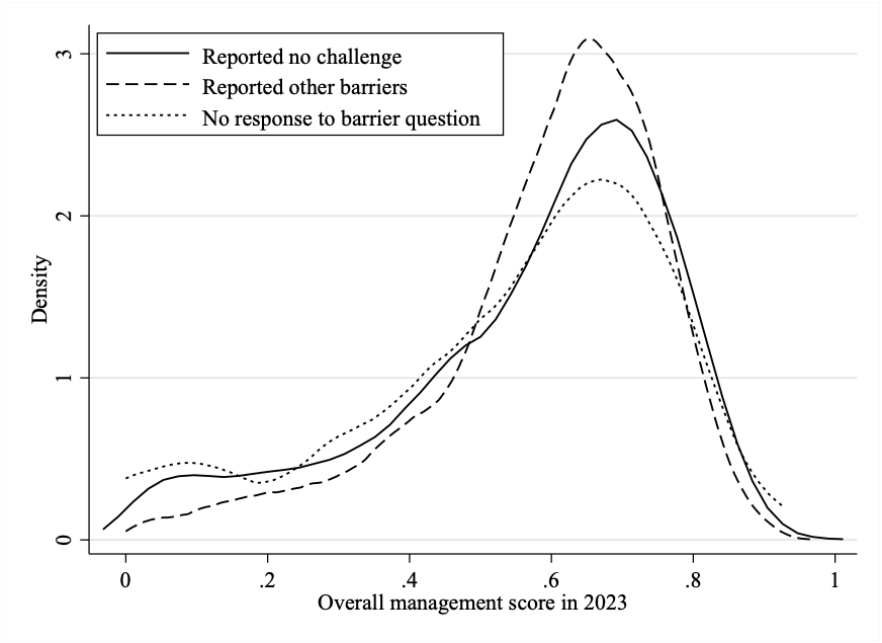


Table A.5: Perception of own performance and awareness of barriers

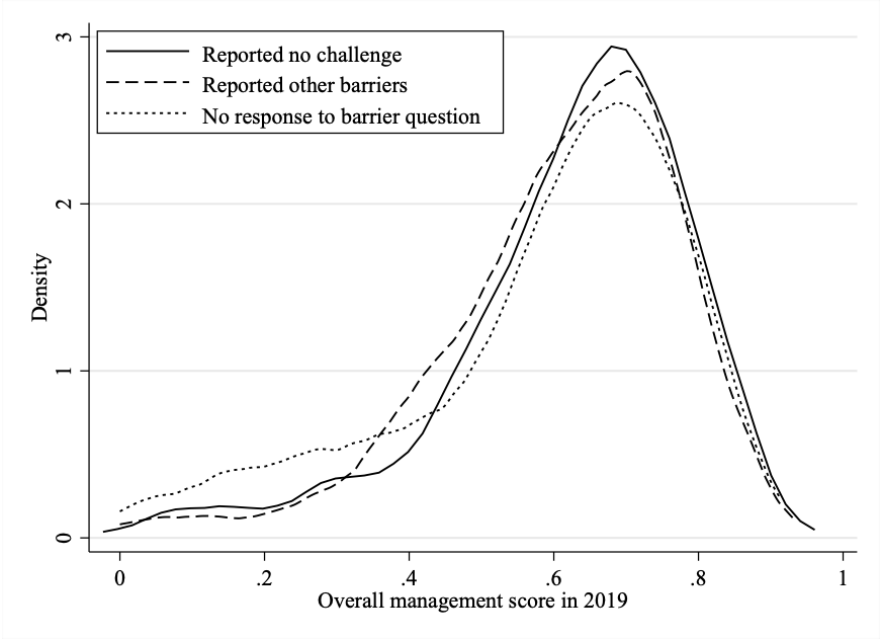
	(1)	(2)	(3)
	Correct prediction of MPS quintile	No challenge	No challenge
Management score	0.327***	-0.141***	-0.132***
	(0.022)	(0.024)	(0.024)
Correct prediction of MPS quintile			-0.026***
			(0.009)
Firm characteristics	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Multiple sites	Yes	Yes	Yes
Observations	14370	14370	14370
R2	0.030	0.017	0.018

Notes: The dependent variable in column (1) is a dummy variable that equals to one if the firm has correctly predicted its management score quintile in MES2023. The dependent variables in columns (2) and (3) are dummy variables that equal to one if the firm has reported that they experienced no challenge in improving the way their business is managed in MES2023. Control variables are in survey year 2023. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.2: Management score distribution by barriers



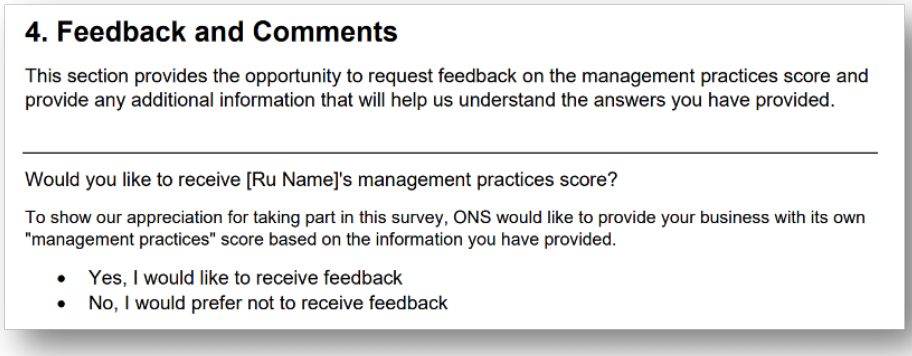
(a) MES 2023



(b) BICS

B Website Contents

Figure B.1: Feedback request question in MES2020



4. Feedback and Comments

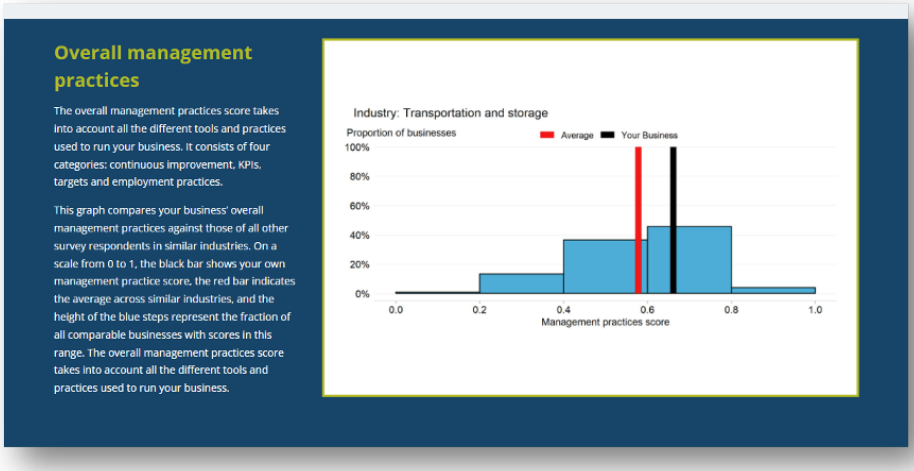
This section provides the opportunity to request feedback on the management practices score and provide any additional information that will help us understand the answers you have provided.

Would you like to receive [Ru Name]'s management practices score?

To show our appreciation for taking part in this survey, ONS would like to provide your business with its own "management practices" score based on the information you have provided.

- Yes, I would like to receive feedback
- No, I would prefer not to receive feedback

Figure B.2: Feedback on the web page



C A Model of Management Improvement with Heterogeneous Barriers

This appendix develops a formal model of firm management improvement decisions that rationalises our empirical findings. We show how heterogeneity in awareness and capacity generates three firm types with distinct behaviors: high-capacity, high-awareness firms that actively improve, low-awareness firms that report "no challenges" despite poor management, and low-capacity firms that recognize gaps but face binding constraints.

C.1 Setup

Firm production. Firm i produces output using a production function that depends on management quality $m_i \in [0, 1]$:

$$Y_i = A_i \cdot f(m_i) \tag{4}$$

where A_i is firm-specific productivity and $f(m_i)$ captures the effect of management practices on output.

Management productivity. $f(\cdot)$ is strictly increasing and concave:

$$f'(m) > 0, \quad f''(m) < 0, \quad \lim_{m \to 1} f'(m) = 0$$

This captures diminishing returns to management quality: poorly-managed firms gain more from improvement than well-managed firms.

Management improvement. Firm i can improve management quality by choosing effort $e_i \geq 0$. Improved management is:

$$m_i' = m_i + g(e_i, \theta_i) \tag{5}$$

where $\theta_i > 0$ is the firm's *capacity* parameter representing managerial resources available for implementation.

Improvement technology. The improvement function $g(e, \theta)$ satisfies:

$$g(0, \theta) = 0 \quad \text{(no improvement without effort)} \tag{6}$$

$$g_e(e, \theta) > 0, \quad g_{ee}(e, \theta) < 0 \quad \text{(diminishing returns to effort)} \tag{7}$$

$$g_\theta(e, \theta) > 0, \quad g_{e\theta}(e, \theta) > 0 \quad \text{(capacity increases effectiveness)} \tag{8}$$

We assume that the cross-partial $g_{e\theta} > 0$. That is, higher capacity makes effort more productive,

creating complementarity between capacity and effort.

Implementation costs. The firm faces implementation costs $c(e_i, \theta_i)$, representing time and resources devoted to improvement:

$$c(e_i, \theta_i) = \frac{\kappa e_i^2}{2\theta_i} \tag{9}$$

where $\kappa > 0$ is a cost scaling parameter. Key properties:

$$c_e = \frac{\kappa e_i}{\theta_i} > 0, \quad c_{ee} = \frac{\kappa}{\theta_i} > 0 \quad \text{(convex costs)}$$

$$c_\theta = -\frac{\kappa e_i^2}{2\theta_i^2} < 0, \quad c_{e\theta} = -\frac{\kappa e_i}{\theta_i^2} < 0 \quad \text{(capacity reduces marginal costs)}$$

Firms with higher capacity face lower marginal costs of effort.

Awareness and perceived returns. Following Gabaix (2019), we assume firms have limited attention and may not fully recognise the returns to management improvement. We model this as sparse attention: firm i perceives the benefit of improved management with attention weight $\alpha_i \in [0, 1]$.

When the firm has awareness parameter α_i, it perceives profit as:

$$\widetilde{\Pi}_i(e_i) = \alpha_i \cdot A_i f(m_i + g(e_i, \theta_i)) + (1 - \alpha_i) \cdot A_i f(m_i) - c(e_i, \theta_i) \tag{10}$$

$\alpha_i = 1$ corresponds to the classical rational firm model. When $\alpha_i \in (0, 1)$, the firm pays partial attention and thus underestimates returns to improvement. This formulation captures the idea that low-awareness firms do not recognise the value of better management practices and genuinely believe there are "no challenges" to address.

C.2 Firm Problem and Solution

The firm chooses effort e_i to maximize perceived profit:

$$\max_{e_i \geq 0} \widetilde{\Pi}_i(e_i) = \alpha_i \cdot A_i f(m_i + g(e_i, \theta_i)) + (1 - \alpha_i) \cdot A_i f(m_i) - \frac{\kappa e_i^2}{2\theta_i} \tag{11}$$

First-order condition. The interior solution (if $e_i^* > 0$) satisfies:

$$\alpha_i \cdot A_i \cdot f'(m_i') \cdot g_e(e_i^*, \theta_i) = \frac{\kappa e_i^*}{\theta_i} \tag{12}$$

where $m_i' = m_i + g(e_i^*, \theta_i)$ is the optimal improved management quality.

From the FOC, we can see that low-awareness firms (α_i small) underestimates benefits and thus chooses less effort. Low capacity firms (θ_i small) also choose less effort, but do so because their marginal cost of effort is high.

Second-order condition. The SOC for a maximum requires:

$$\alpha_i A_i [f''(m_i')g_e^2 + f'(m_i')g_{ee}] - \frac{\kappa}{\theta_i} < 0 \tag{13}$$

This is satisfied given our assumptions about $f(m)$ and $g_(e, \theta)$.

Corner solution. The firm chooses $e_i^* = 0$ if the marginal benefit at $e = 0$ is less than the marginal cost at $e = 0$. Since $c_e(0, \theta_i) = 0$, the corner solution occurs when:

$$\alpha_i \cdot A_i \cdot f'(m_i) \cdot g_e(0, \theta_i) \leq 0 \tag{14}$$

Given that $f'(m_i) > 0$ and $g_e(0, \theta_i) > 0$ for all θ_i, this reduces to:

$$e_i^* = 0 \quad \text{if and only if} \quad \alpha_i = 0 \tag{15}$$

C.3 Comparative Statics

We now derive how optimal effort responds to the firm's characteristics. Throughout, we assume an interior solution ($e_i^* > 0$).

Effect of current management quality m_i.

Taking the total derivative of the FOC with respect to m_i:

$$\alpha_i A_i [f''(m_i')(1 + g_e \frac{de^*}{dm_i})g_e + f'(m_i')g_{ee}\frac{de^*}{dm_i}] = \frac{\kappa}{\theta_i}\frac{de^*}{dm_i} \tag{16}$$

Collecting terms with $\frac{de^*}{dm_i}$:

$$\frac{de^*}{dm_i} = \frac{-\alpha_i A_i f''(m_i')g_e^2}{\alpha_i A_i [f''(m_i')g_e^2 + f'(m_i')g_{ee}] - \kappa/\theta_i} \tag{17}$$

The denominator is negative by the SOC. The numerator is positive since $f''(m) < 0$ and $g_e > 0$. Therefore:

$$\frac{\partial e^*}{\partial m_i} > 0$$

.

Prediction 1 (Positive selection): Firms with higher current management quality m_i exert more effort to improve, holding other factors constant.

This result initially seems counterintuitive since $f''(m) < 0$ implies diminishing returns—poorly-managed firms have more to gain per unit improvement. However, the positive relationship arises because m_i is correlated with capacity θ_i and awareness α_i in equilibrium (we show this below).

Effect of capacity θ_i.

Taking the total derivative of the FOC with respect to θ_i:

$$\alpha_i A_i[f''(m_i')g_e g_\theta + f'(m_i')(g_{e\theta} + g_{ee}\frac{de^*}{d\theta_i})g_e] = \frac{\kappa}{\theta_i}\frac{de^*}{d\theta_i} - \frac{\kappa e^*}{\theta_i^2} \tag{18}$$

Rearranging:

$$\frac{de^*}{d\theta_i} = \frac{\alpha_i A_i f'(m_i')g_{e\theta}g_e + \alpha_i A_i f''(m_i')g_e g_\theta + \kappa e^*/\theta_i^2}{\kappa/\theta_i - \alpha_i A_i[f''(m_i')g_e^2 + f'(m_i')g_{ee}]} \tag{19}$$

The denominator is positive by the SOC (with sign reversed). In the numerator: $\alpha_i A_i f'(m_i')g_{e\theta}g_e > 0$ while $\alpha_i A_i f''(m_i')g_e g_\theta < 0$ (but typically small). Finally, $\kappa e^*/\theta_i^2 > 0$. For reasonable parameter values, the numerator is positive. Therefore:

$$\frac{\partial e^*}{\partial \theta_i} > 0$$

Prediction 2 (Capacity effect). Firms with higher capacity θ_i exert more effort to improve.

Higher capacity has two effects: (1) it makes effort more productive ($g_{e\theta} > 0$), increasing marginal benefits, and (2) it reduces marginal implementation costs ($c_{e\theta} < 0$). Both channels increase optimal effort.

Effect of awareness α_i.

Taking the total derivative of the FOC with respect to α_i:

$$A_i f'(m_i')g_e + \alpha_i A_i[f''(m_i')g_e^2 + f'(m_i')g_{ee}]\frac{de^*}{d\alpha_i} = \frac{\kappa}{\theta_i}\frac{de^*}{d\alpha_i} \tag{20}$$

Rearranging:

$$\frac{de^*}{d\alpha_i} = \frac{A_i f'(m_i')g_e}{\kappa/\theta_i - \alpha_i A_i[f''(m_i')g_e^2 + f'(m_i')g_{ee}]} \tag{21}$$

The numerator is positive. The denominator is positive by the SOC (with sign reversed). There-

fore:

$$\frac{\partial e^*}{\partial \alpha_i} > 0$$

.

Prediction 3 (Awareness effect): Firms with higher awareness α_i exert more effort to improve.

Higher awareness means the firm perceives a larger fraction of the true benefits of management improvement. This directly increases the perceived marginal benefit of effort, leading to higher optimal effort. Firms with $\alpha_i \approx 0$ perceive almost no benefit and choose effort near zero.

Note that *capacity* affects both the benefit (through $g_{e\theta}$) and the cost (through $c_{e\theta}$), whereas *awareness* only affects the perceived benefit (multiplicatively scaling the entire benefit term). This means awareness has a particularly strong effect when baseline returns are high (high A_i, low m_i), while capacity effects are more uniform.

C.4 Three Firm Types

We now show how the model generates three distinct firm types based on the joint distribution of (θ_i, α_i).

High-capacity firms. These firms have high θ_i and high α_i. From Predictions 2 and 3: These firms choose high $e_i^* > 0$.

The FOC shows that high awareness means they perceive most of the benefit:

$$\alpha_i \cdot A_i f'(m_i') g_e(e_i^*, \theta_i) = \frac{\kappa e_i^*}{\theta_i}$$

With α_i close to 1, they see the full marginal benefit. High θ_i reduces marginal costs and increases g_e through complementarity.

Empirically, high e_i^* translates into requesting feedback, visiting the website for more information, signing up for mentoring purchasing consulting services and taking wider improvement actions.

Observable correlates include higher m_i (due to past improvements), higher share of managers (proxy for θ_i), more educated managers (proxy for both θ_i and α_i).

Low-awareness firms. These firms have moderate or high θ_i but low $\alpha_i \approx 0$.

From Prediction 3 and the corner solution condition: Low α_i means the firm perceives almost no

benefit from improvement. Even if they have capacity (θ_i not too low), they choose $e_i^* \approx 0$ because:

$$\lim_{\alpha_i \to 0} \alpha_i \cdot A_i f'(m_i') g_e(e, \theta_i) = 0 < \frac{\kappa e}{\theta_i} \quad \forall e > 0$$

The perceived marginal benefit vanishes, so no positive effort is worthwhile. Empirically, we expect these firms not to request feedback or take other improvement actions. When asked about barriers, we expect them to report "no challenges".

Observable correlates include lower m_i (lack of past improvement), but not necessarily different capacity measures. The key distinguishing feature is stated barriers: they report "no challenges."

Low-capacity firms. These firms are characterised by high/moderate α_i but low θ_i.

From Prediction 2: Low θ_i reduces optimal effort through two channels in the FOC:

$$\alpha_i \cdot A_i f'(m_i') g_e(e_i^*, \theta_i) = \frac{\kappa e_i^*}{\theta_i}$$

Even though awareness is high (α_i close to 1), binding capacity constraints prevent action. In the extreme:

$$\lim_{\theta_i \to 0} \frac{\kappa e_i^*}{\theta_i} = +\infty$$

, so that $e_i^* \to 0$ even with perfect awareness.

Low-awareness firms do not perceive benefits (low α_i); low-capacity firms perceive benefits but cannot act (low θ_i). Both choose low effort, but for fundamentally different reasons. Low-capacity firms would like to improve but cannot. They are less likely to respond even to survey questions (responding itself requires time and capacity). When they do respond, they cite time and resource barriers (accurately reflecting their constraint).

Observable correlates: Lower m_i, lower share of managers (low θ_i), less educated managers (low θ_i), high non-response rates to surveys.

C.5 Linking to Observable Behavior

To connect the model to our empirical proxies, we specify how latent effort choice maps to observable actions.

Requesting feedback. Let $R_i \in \{0, 1\}$ indicate whether firm i requests feedback. This is an

observable signal of intention to improve. We model it as:

$$R_i = \mathbf{1}[e_i^* > \bar{e}]$$

where $\bar{e} > 0$ is a threshold level of intended effort needed to motivate requesting information.

From our comparative statics:

$$\Pr(R_i = 1) = \Pr(e_i^* > \bar{e})$$

This probability is increasing in both θ_i and α_i. Moreover, since e_i^* is increasing in m_i when θ_i and α_i are positively correlated with m_i, we get:

$$\Pr(R_i = 1 \mid m_i \text{ high}) > \Pr(R_i = 1 \mid m_i \text{ low})$$

. This generates the positive correlation between R_i and m_i observed in Table 3.

Actual improvement. Let $\Delta m_i = m_i' - m_i$ be the realized improvement. From equation (2):

$$\Delta m_i = g(e_i^*, \theta_i)$$

. This is increasing in e_i^*, which is increasing in both θ_i and α_i. Crucially, the Gabaix (2019) formulation gives us a clean interpretation of the "intention effect" we observe in the 2016 natural experiment: requesting feedback signals high α_i (firm is paying attention to management). From the FOC:

$$e_i^* = \frac{\theta_i}{\kappa} \alpha_i A_i f'(m_i') g_e(e_i^*, \theta_i)$$

. Therefore, even without receiving information, firms with high α_i (who request feedback) choose higher effort. This generates the positive association between requesting feedback and improvement in Table 4, column (2), even though no feedback was actually delivered in 2016.

Self-reported barriers. Let B_i be the self-reported barrier. We model this as:

$$B_i = \begin{cases} \text{"No challenges"} & \text{if } \alpha_i < \bar{\alpha} \\ \text{"Time/resources"} & \text{if } \alpha_i \geq \bar{\alpha} \text{ and } \theta_i < \bar{\theta} \\ \text{Other/none} & \text{if } \alpha_i \geq \bar{\alpha} \text{ and } \theta_i \geq \bar{\theta} \end{cases} \tag{22}$$

The key insight from the Gabaix formulation: low-awareness firms report "no challenges" because they genuinely perceive no benefit ($\alpha_i \approx 0$ means they are inattentive to management). This maps naturally to our finding in Figure 7. Low-capacity firms, by contrast, perceive the benefit (α_i high) but face binding constraints (θ_i low), so they accurately report time/resource barriers.

Survey non-response. Let $S_i \in \{0, 1\}$ indicate survey response. Responding requires time and cognitive resources, which are constrained by θ_i:

$$\Pr(S_i = 1) = \Pr(\theta_i > \theta_{\text{survey}})$$

where θ_{survey} is the capacity threshold needed to complete the survey. This generates the negative correlation between non-response and management quality (Table 6) if m_i is correlated with θ_i. Importantly, awareness α_i doesn't directly affect survey response in this formulation—even low-awareness firms can respond if they have capacity. What matters for response is whether the firm has sufficient managerial bandwidth, not whether they recognize management gaps.

C.6 Correlation Structure and Positive Selection

The model generates positive selection if current management quality m_i is positively correlated with capacity θ_i and awareness α_i. We now show how this correlation arises endogenously.

Suppose management quality evolves according to:

$$m_{i,t+1} = m_{i,t} + g(e^*_{i,t}, \theta_i) + \varepsilon_{i,t}$$

where $\varepsilon_{i,t}$ is an idiosyncratic shock. From our comparative statics, $e^*_{i,t}$ is increasing in both θ_i and α_i. Therefore, firms with higher θ_i and α_i improve more each period, generating a positive correlation between $m_{i,t}$ and (θ_i, α_i) even if these parameters are initially uncorrelated.

This cumulative advantage mechanism explains why better-managed firms (high m_i) tend to have higher capacity and awareness, are more likely to seek further improvement (inducing *positive selection* and why the management distribution exhibits persistence with mean reversion (high-m firms improve less from a given change, but seek more changes).

C.7 Model Predictions and Empirical Evidence

We now state the model's predictions and map them to our empirical findings.

Prediction 1 (Positive selection). Better-managed firms exert more effort to improve.

Evidence. Table 3 shows that management score is strongly positively associated with requesting feedback (columns 1-2), visiting the website (column 3), using consulting services (column 4), and taking improvement actions (column 5). The effect is robust across all measures and specifications.

Prediction 2 (Capacity effects). Firms with higher capacity (more managers, better-educated managers) exert more effort.

Evidence. Table 3 shows that share of managers and share of managers with degrees are positively associated with all improvement behaviors. Table 4 shows these variables predict actual improvement in management scores.

Prediction 3 (Awareness effects). Firms with lower awareness choose $e^* = 0$ and report "no challenges."

Evidence. Figure 7 shows 53% of firms report no barriers despite wide variation in management quality, consistent with low awareness preventing recognition of gaps.

Prediction 4 (Intention matters). Even without information treatment, high-awareness firms improve because they are primed to act.

Evidence. Table 4 column (2) shows that requesting feedback predicts improvement even when feedback was not delivered (2016 natural experiment), indicating self-selection on readiness to act (α_i).

Prediction 5 (Capacity constraints bind for low-θ firms). Low-capacity firms are less likely to respond to surveys and cite time/resource barriers when they do.

Evidence: Table 6 shows firms with lower management scores (correlated with lower θ_i) are significantly less likely to respond to the barriers question. Figure 7 shows that among responders, 15% cite time constraints and 12% cite resource constraints.