Skills combinations and firm performance

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Abstract Creative skills, STEM (science, technology, engineering and mathematics) skills and management skills have all been positively associated with firm performance as well as regional growth. But do firms that combine these types of skills in their workforce grow more quickly than those that do not? We compare the impact of STEM, creative and management skills on their own, and in various combinations, on turnover growth. We use a longitudinal dataset of UK firms over the period 2008–2014 with lagged turnover data to explore whether the combination of skills used by a firm impacts its future turnover growth. Using fixed-effect panel and pooled OLS models, we find that the performance benefits associated with both STEM and creative skills materialize when they are combined with each other or with management skills rather than when they are deployed on their own.

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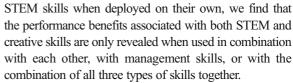
1 Introduction

This paper explores the impact of creative, technical and management workforce skills, and their combinations, on firm growth. There is a widely accepted link between levels of human capital and economic performance at the geographical level (e.g. Toner 2011). Consequently, policymakers have sought to encourage the development of specific types of workforce skills. In particular, recent decades have seen a substantial emphasis on the encouragement and promotion of science, technology, engineering and mathematics (STEM) education (Atkinson and Mayo 2010). Indeed, growing evidence suggests that the presence of STEM workers is associated with increased productivity, rising wages and higher levels of innovation at the regional level (Atkinson and Mayo 2010; Peri et al. 2015; Winters 2014). Concurrent but distinct to the STEM phenomenon, there has been an increasing recognition of the economic importance of creative workers. This originally stemmed from Florida's work (2002; 2004), which argued that the presence of 'bohemians', or artists and related cultural amenities, were drivers of innovation and regional growth. Subsequent research has explored the impact of these workers' skills on performance at a regional level (McGranahan and Wojan 2007; Wojan et al. 2007; Wedemeier 2010; Huggins and Clifton 2011; Marrocu and Paci 2012; Lee and Rodríguez-Pose 2014; Wojan and Nichols 2018). In parallel, the role

played by management skills (or lack thereof) in explaining persistent stagnation and declines in productivity in OECD economies has been debated (Bloom et al. 2019). While debates on STEM, creative and management skills remained separate for some time, the growing realisation that there may be complementary effects between these skills led them to increasingly converge over recent years. This has manifested in the rise of a movement advocating to add arts to STEM education, resulting in 'STEAM'—science, technology, engineering, *arts*, and mathematics—curricula (Daugherty 2013), which has coincided with growing evidence about the interactive effects of STEM and creative occupations at the regional level (Brunow et al. 2018).

While the association between skills and regional growth is now well-established, there has been comparatively less work on the impact of skills, and skills combinations, on firm performance. Therefore, evidence on the benefits firms can attain by investing in STEM (see Leiponen 2005; Coad et al. 2014) and creative skills (Mollick 2012) is limited. By contrast, recent contributions to the literature on the economics of management practices (Bloom and van Reenen 2007; Bloom et al. 2019) point to the importance of management skills for firm performance. Despite the relative shortage of evidence on the performance implications of firms' investments in specific workforce skills, there is growing interest in understanding the impact of skills *combinations*. In their research on a UK creative cluster, Sapsed et al. (2013) find that firms combining STEM and creative skills outperform those that specialise in just one of those types of skills. These findings found further support in a study that investigated the broader population of UK firms in Siepel et al. (2016).

The aim of this paper is, therefore, to contribute evidence on the impact of investments in STEM, creative and management skills—and various combinations thereof—on firm performance. In particular, following an exploratory approach, we aim at understanding the impact of utilising, and combining, these skills on turnover growth. We do so by analysing a panel dataset of firms obtained by combining data from two official UK datasets. We use three waves of the UK Innovation Survey (2008–10, 2010–12 and 2012–14) and combine these with annual turnover data from the administrative Business Structure Database. Using fixed effects and pooled OLS methods, we model the impact of the use of skills and skill combinations on future firm performance. While we find limited effects on performance when we consider creative or

STEM skills when deployed on their own, we find that the performance benefits associated with both STEM and creative skills are only revealed when used in combination with each other, with management skills, or with the combination of all three types of skills together.

This paper makes two contributions to the literature. It is the first study—to our knowledge—to compare the differential impacts of STEM, creative and management skills on firm performance. Second, it is the first to examine the impact of various combinations of these skills. In doing so, it sheds light on which combinations of skills are particularly valuable to firms, informing policies on education and training. The paper highlights that the performance benefits of the use of creative and STEM skills are better explained by the presence of skills in combinations—with each other and with management skills. Consequently we offer support to policies encouraging investments in the combination of skills as a means to expedite growth. The remainder of the paper is organized as follows: in Section 2, we review extant literature on skills and firm growth, as well as studies on skill combinations. We then illustrate data and methodology in Section 3, before presenting results in Section 4. Finally, Section 5 discusses the implications of our findings, highlighting the key limitations of the study and possible avenues for future research.

2 Background literature

2.1 Skills and firm growth

This paper explores the impact of workforce skills on firm growth. In doing so, it positions our work in the broader literature on firm growth. As discussed in Audretsch et al. (2014), studies on firm growth have tended to focus on three main topics: testing and application of Gibrat's Law of Proportionate Effects (1931), which assumes that firm growth rates closely approximate a random walk; the effect of external factors; and the effects of endogenous and/or strategic characteristics of the firm (Geroski 1999). This paper takes the final approach, exploring the effect of combinations of skills on firms' turnover growth. Such approaches are empirically challenging in that these endogenous factors have only limited explanatory power over firm performance in comparison with the effectively random 'inevitable trading vicissitudes' involved in running a business (Coad et al. 2013). In particular, a firm's

investment in a combination of skills will be made strategically, with the hope of driving subsequent growth. However, as firms grow and mature, the explanatory power of factors such as resources will improve, as in Penrose's words, 'the heterogeneity of the productive services available or potentially available from its resources that gives each firm its unique character' (Penrose 1959, p. 75). This provides the basis for our examination of the impact of workforce skills on firm performance.

2.1.1 Skills recombination and firm performance

Knowledge is one of the most strategic resources firms can build on to earn superior rents and achieve a sustainable competitive advantage (Grant 1996a; Kogut and Zander 1992). Firms' ability to harness and integrate the specialized knowledge and skills of their employees in distinctive ways, rather than the knowledge and skills themselves, is what may allow them to gain and sustain a competitive advantage (Grant 1996b). The greater the variety of knowledge and skills held by individuals, the higher the chances for firms to generate combinations that are novel and difficult to imitate (Lippman and Rumelt 1982). As a result of the cognitive diversity stemming from the interaction among individuals with different knowledge and skills (Dougherty 1992), firms have a greater ability to absorb and exploit external knowledge and to exchange and combine internal one (Cohen and Levinthal 1990), making novel associations and experimenting with new solutions (Nahapiet and Ghoshal 1998; Smith et al. 2005).

The importance of firms' 'combinatory' activities was already underscored by Schumpeter (1934), for whom innovations were essentially 'new combinations' of knowledge and resources. By pointing at knowledge recombination as a key source of novelty (Fleming 2001; Rosenkopf and Nerkar 2001; Stark 2011) and at firms' recombinant capabilities from broad knowledge bases as a key driver of firms' performance (Breschi et al. 2003; Galunic and Rodan 1998; Hargadon and Sutton 1997; Yayavaram and Ahuja 2008), both the innovation and strategy literatures have echoed Schumpeter's view of recombination as the engine of innovation. This is supported by evolutionary economic perspectives that argue that firms that have access to a broad range of knowledge and skills tend to be more innovative (Breschi et al. 2003; Suzuki and Kodama 2004), widening the scope of their search activities and, thus, improving the basis for the identification of complementarities that enable novel combinations (Dosi 1988; Nelson and Winter 1982; Quintana-

García and Benavides-Velasco, 2008). More recently, Carnabuci and Operti (2013) have highlighted that the diversity of a firm's technological knowledge may critically influence its ability to innovate via recombination, although whether this holds when integrating other types of knowledge is unknown.

While the link between firms' knowledge diversity and innovation is intuitive from an evolutionary economic standpoint, whether and how this translates into superior performance in terms of employment or sales growth is considerably less clear. Empirical evidence is mixed and shows that innovation does not necessarily lead to firm growth (Audretsch et al. 2014; Coad and Rao 2008; Coad et al. 2014) as there are many factors contributing to firm performance, with innovation being only one of them. Yet, Schumpeterian models of innovation require not just recombination but the ability to bring novel solutions to the market, which Schumpeter identified as the role of the entrepreneur (Schumpeter 1934). Managerial skills are, hence, required to capture value from innovations (Teece 1986), and, more broadly, to enhance firm performance (e.g. Cooper et al. 1999; Siepel et al. 2017).

2.2 Creative, STEM and management skills

The discussion above provides a broad rationale for the combination of skills as a driver of firm growth. As previously highlighted, this paper focuses on three broad types of skills: STEM (science, technology, engineering and mathematics), creative and management skills. While these skills have been studied on their own and in combinations (see Table 1 for a summary), it is important to clarify how we define them for our subsequent analysis. The following sections, therefore, discuss each type of skill and related identification issues, as well as previous research on the topic.

2.2.1 STEM skills and firm performance

There is a growing body of literature that attempts to quantify the benefits of science, technology, engineering and mathematics (STEM) skills at the regional level (e.g. Winters 2014; Peri et al. 2015; Wright et al. 2017; Brunow et al. 2018). In this literature, STEM skills are generally proxied by the number of workers with a STEM background in a particular city or region. However, the definitional issue around STEM skills becomes more difficult in research at the firm level. Here, there is often an equivalence made between the presence of workers with a STEM

Table 1 Summary of the literature on combinations of skills

Skill/skills combination		Publication	Level of analysis	Findings
STEM skills		Leiponen (2005)	Firm	STEM investment is formally complementary to R&D and innovation
		Coad et al. (2014)	Firm	STEM investment is positively associated withinnovation and firm growth
		Winters (2014)	Region	STEM skills are associated with regional growth
		Peri et al. (2015)	Region	Foreign STEM workers increased productivity in cities
Creative skills		Mollick (2012)	Firm	Creative skills are significantly associated with performance in the computer games industry
		Marrocu and Paci (2012)	Region	Creative graduates contribute more to economic performance than non-creative graduates or bohemians.
		Lee and Rodríguez-Pose (2014)	Region	Creative occupations drive innovation but creative industries firms are not necessarily more innovative
		Wojan and Nichols (2018)	Firm, Region	Rural creative or design focused firms are concentrated in areas with performing arts organizations. Regions with these firms have higher wage growth.
Management skills		Bloom and van Reenen (2007)	Firm	Management practices are significantly associated with firm performance in a variety of settings
		Bloom et al. (2019)	Firm	
Skills combinations	Creative and STEM	Sapsed et al. (2013)	Firm	Creative and STEM skills are associated with better performance in creative and digital firms in a UK clusters
		Siepel et al. (2016)	Firm	Creative and STEM skills are positively associated with innovation and firm performance in all sectors
		Brunow et al. (2018)	Firm, Region	STEM and creative workers associated with increased innovation and regional spillovers for STEM workers
	Creative and Management	Mollick (2012)	Firm	Management plays a more important role for growth in computer games firms than does creative skills
	STEM and Management	Siepel et al. (2017)	Firm	Access to management skills has a long-run impact on the performance on technology firms, regardless of investment in technology.

background and the execution of STEM-related tasks. While there is evidence of a positive association between share of STEM graduates employed in a firm and innovation (Leiponen 2005) and subsequent firm performance (Coad et al. 2014), this does not necessarily mean that those workers are actually doing STEM work, or utilising STEM skills. For instance, recent work by Deming and Noray (2018) suggests that the nature of relevant STEM skills shifts rapidly with technological change, so STEM skills that were previously desirable often become obsolete, requiring workers to either reskill, or to move to other non-technical roles in organisations. Hence, the best way to identify STEM skills is either to ask firms directly about their use of skills or to rely on standard classifications, such as the O*NET classification,[1] which maintains a specific list of STEM occupations, to match the tasks done by workers. As illustrated in Section 3, we do the former.

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[1] See https://www.onetonline.org/

2.2.2 Creative skills and firm performance

Classifying skills as 'creative' poses an instant challenge as virtually all occupations require some degree of creativity—see for instance Goldman et al. (2016) on the impact of creativity training for STEM workers, and National Academies of Science (2018) for a discussion of creativity as it relates to STEM skills. In light of this, we make the distinction between creativity (which is applicable to virtually all skills and occupations and is itself crucial for innovation, see for instance Anderson et al. 2014 for a summary) and 'creative skills', which we define as those which have been classified as being associated with occupations with a substantial creative component (for instance the O*NET or HEFCE/DBIS classifications in the US and UK, respectively). Such definitions have been used in research on the impact of 'creative skills' at the regional, rather than at the firm level—starting with the work of Florida (2002). This work has been followed by subsequent research on the role of creative milieu—that is, presence of workers with arts background or with arts occupations—and the impact on firms' economic performance (e.g. Glaeser 2005; Wojan et al. 2007; McGranahan and Wojan 2007; Marrocu and Paci 2012; Lee and Rodríguez-Pose 2014). Among firm-level analysis, in a study of performance in the gaming sector, Mollick (2012) investigated the impact of individuals in creative or managerial roles on firm performance. More recently, Wojan and Nichols (2018) explored the impact of arts- and design-oriented firms in regional areas using firm-level data. Compared to the literature on STEM and management skills, there is relatively little evidence on the impact of creative skills per se on firm performance, and the existing evidence is mixed. For instance, Siepel et al. (2016) find that use of creative skills alone has no impact on firm performance or innovation outcomes. In contrast, Brunow et al. (2018) find limited positive impacts on innovation outcomes for firms employing creative workers, but the effect identified is smaller than the interaction effect of creative and STEM skills together.

2.2.3 Management skills and firm performance

Despite the vast volume and scale of the academic management literature, the clearest direct discussion of the impact of managerial practices on firm performance has come from economists studying management practice. In particular, the work of Bloom, van Reenen and colleagues (Bloom and van Reenen 2007; Bloom et al. 2019) has documented the impact of management practices on firm performance, generally finding evidence supporting the link between improved managerial practice and firm performance. Much of this literature has been based on analysis of surveys of managerial practice, such as the US Managerial and Organizational Practices Survey (MOPS) (see Bloom et al. 2019) and the UK Management and Expectations Survey (see ONS 2018). Beyond this, there are a range of studies that explore the impact of particular 'disciplinary' practices on performance (Huselid 1995; Laursen and Foss 2003 for HR; Kaynak 2003 for operations; Cooper et al. 1999 for R&D management; Chiva and Alegre 2009 for design management). Despite tremendous heterogeneity among practices, there is a clear link between management practices and firm performance.

2.2.4 Combinations of STEM, creative and management skills and firm performance

As discussed in Section 2.1.1, although the reason why the combination of skills may subsequently generate firm growth is intuitive, the evidence on this topic is limited. Sapsed et al.'s (2013) study of a creative, digital and IT cluster in the UK found that firms that 'fused' creative and technical skills outperformed those utilising only one or the other. Siepel et al. (2016) found a similar effect across sectors in the UK. Analogously, Brunow et al. (2018) showed that the combination of creative and science skills is associated with higher levels of innovation.

Evidence is fairly scarce also as concerns the combination of STEM and management skills. This has a strong intuitive basis in Schumpeterian thought (e.g. Schumpeter 1934), as seen in linear models of innovation according to which technologies require entrepreneurial action to be commercialised (see for instance Fagerberg 2005 as well as Pavitt 1998 for a concordant, if non-Schumpeterian, view). Among empirical literature, there is clear evidence of a correlation between STEM skills, R&D spending and innovativeness (Leiponen 2005), as well as evidence about the positive impact of management practices

on firms' innovation activities (e.g. Laursen and Foss 2003). Some counterfactual evidence is provided in Siepel et al. (2017), who show that, irrespective of technical skills, access to managerial skills is vital for the long-run growth and survival of high-tech firms. In this sense, there are both theoretical and empirical bases to assume that managerial skills are essential for the commercialisation of technological innovations.

Evidence on the link between creative and management skills is also limited. There is substantial historical evidence about the role of management in creativity-dependent sectors—see for example Schatz's (1996) 'genius of the system' argument in his study of golden-era Hollywood. However, there are relatively few robust empirical studies. Chiva and Alegre (2009) explore the use of design management practices and find these to be positively associated with firm performance. Mollick (2012) finds that managerial capability contributes more to performance than creative skills in the computer gaming sector, although both adding significantly to performance. Although this suggests that managerial skills may 'unlock' benefits associated with creative skills, there is a need for more evidence on their combinatory effect.

Finally, a different approach to explore skills combination may be seen in the work of Asheim and colleagues (Asheim and Coenen 2005; Asheim and Isaksen 2002), who use a different nomenclature to propose three distinct ways of working, with particular (but not exclusive) reference to knowledge at the regional level. They highlight *synthetic* knowledge (broadly relating to technical or scientific knowledge); *symbolic* knowledge (relating to creative knowledge) and *relational* knowledge (relating to interactions and management). The literature drawing upon this framework (see for instance, Pina and Tether 2016; Tether et al. 2012,) uses these to contrast vastly different types of knowledge, and also to explore the role of different types of knowledge that an organisation might use to drive innovative behaviour (Grillitsch et al. 2019).

The lack of comprehensive studies focusing on the co-existence of multiple skills at firm level significantly limits our understanding of the relationship between workforce skills and firm performance, with the risk of overemphasising the role

of one type of skills and neglecting the existence of complementarities between different types. This paper tries to address this gap by exploring whether the use of STEM, creative and managerial skills, both individually and in conjunction with each other is associated with higher firm performance.

3 Data and method

3.1 Data

The data we use in our analysis come from two official UK datasets: the UK Innovation Survey (UKIS) and the Business Structure Database (BSD). The UKIS (ONS 2017) is a biannual survey that is the UK's version of the Community Innovation Survey, which captures innovative activities of innovative and non-innovative firms across Europe. The UKIS covers a weighted sample of firms with more than ten employees across the economy, with greater emphasis on firms in more technology-intensive sectors. For our analysis, we use the three waves of the UKIS—the 7th, the 8th and the 9th wave—which surveyed firms about their innovation activities from 2008 to 2010, from 2010 to 2012 and from 2012 to 2014, respectively. We chose to start with the 7th wave of UKIS because it was the first one to ask each firm whether it had used a number of skills in the period of reference, allowing us to measure our main independent variables. The UK Innovation Survey is not specifically designed to be a fully longitudinal survey; instead, it includes a 'mini-panel' where some firms in previous surveys are contacted again. This means that not all the firms in the sample are not necessarily tracked over time. Nonetheless, a number of firms in the sample remain the same across waves, and these firms are denoted by the same identifier over time. We exploited this characteristic of the UKIS dataset in order to build a panel of firms by including those firms which appeared in at least two of the three survey waves we considered.

One major drawback of using UKIS data is that data on performance (i.e. turnover) are self-reported and partially incomplete. This is especially problematic for studies based on panel datasets which intend to account for longer-term effects on firm performance. In order to

cope with this issue, we linked the UKIS data with the panel of the UK Business Structure Database (BSD) (Department for Business Innovation and Skills, et al. 2018). The BSD is a comprehensive database of all firms registered in the UK who pay National Insurance or Value-Added Tax (VAT). The dataset includes employment figures derived from National Insurance records and turnover derived from VAT records. In the case of the data used here, we were able to match UKIS data to the BSD, providing us with more comprehensive records for firm performance (and in particular firms' turnover) during the periods of observation (i.e. 2008–10; 2010–12; 2012–14) and after (i.e. 2014–16), allowing us to consider the impact of skills on subsequent performance. We used turnover to create several variables that will be used in our regression models, such as firm growth and indicators such as R&D intensity. This process yielded us a sample of 9540 firms. However, the existence of missing values in some key variables of UKIS reduced our sample to 5350 firms.[2]

3.2 Methodology

In order to investigate the effect of skills combinations on firm performance, we estimate the following model:

$$\text{Growth}_{i,t} = \alpha + \text{SKILLS}_{i,t-1}\beta + Z_{i,t-1}\gamma + \delta_t + \eta_i + \varepsilon_{i,t} \quad (1)$$

Where i and t refer to firm and time respectively; $\text{SKILLS}_{i,t-1}$ denotes our main estimators based on skills used by the firm and their combinations; $Z_{i,t}$ is a vector of control variables (including the log of turnover in period $t-1$); δ_t denotes a series of time period dummies; η_i represents unobserved firm-specific effects; $\varepsilon_{i,t}$ and is the error term.

Given the nature of our data, each period t represents one wave of UKIS which covers a time span of 3 years (2008–10; 2010–12; and 2012–14). As a consequence, our independent variables and controls refer to these 3-year periods. To be consistent also, our dependent variable was measured accordingly, by considering the turnover growth in the 3 years following the period in which the skills were used (i.e. 2010–12; 2012–14; and 2014–16).[3]

The specification of our model takes the form of an augmented Gibrat law panel data model in which the initial level of turnover and other variables are regressed on subsequent turnover growth (Sutton 1997; Calvo 2006; Stam 2010) using panel regression with fixed effects (FE) and pooled ordinary least squares (OLS). The time lag between the use of the skills by the firms and the measure of firm growth is also a way to partially alleviate reverse-causality concerns. It is true that high-growth firms may be more likely to invest in skills and introduce organizational changes (Athey and Stern 1998). However, this issue is attenuated by the introduction of a time lag between our independent and dependent variables (Caroli and Van Reenen 2001, Coad et al. 2016a, b). In addition, other concerns about the potential bias produced by time invariant regressors and unobserved heterogeneity are mitigated by the implementation of FE models. Finally, we control for potential time-specific effects by using time dummies.[4] Nevertheless, we acknowledge that despite all these efforts, endogeneity cannot be fully ruled out in our case, and that the aim of this paper is not to identify casual effects, but instead to reveal interesting associations among variables.

While panel FE regressions represent the most appropriate approach to analyse our data, which is also confirmed by the Hausman test, we estimate both panel FE regressions and pooled OLS regressions. This is because since our main source of data (UKIS) is not specifically designed to be a longitudinal study, we are only able to perform panel regressions on an unbalanced panel. In particular, even though all the firms in the sample have been selected because they took part in at least two waves of the survey, the presence of missing values in some key variables of UKIS leads to cases in which certain firms end up being observed only once, and hence are excluded from the calculation of the FE regression coefficients. As a consequence, while the pooled OLS regressions will be based on all data points available in our sample (i.e. 5350 firms and 6842 observations), the panel FE regressions will be performed on a sample of 1267 firms and 2759 observations.

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[2] We compared the initial sample and the one without missing values on the basis of several dimensions (e.g. firm size, growth, sector, region) and we found that there are no significant differences between the two samples.

[3] For example, in the case of the turnover growth measured in the period 2014–16, our regressors refer to the period 2012–14.

[4] We acknowledge that some of the early years in our panel coincide with the recession which followed the financial crisis of 2008. However, our analysis extends beyond this particular period and covers a time span from 2008 to 2014 (up to 2016 as regards the growth of the firm). Moreover, the use of the time dummies should control for the heterogeneity of these time-related trends.

3.3 Measuring the use of skills

We highlighted in Section 2.2 some of the challenges with identifying skills. Here, we discuss our rationale for measuring the use of skills. We primarily draw upon a new series of questions introduced in the 7th UKIS, which asked firms if they had accessed any of a number of skills in the period of reference, including *design*, *engineering*, *graphics*, *mathematics*, *multimedia* and *software design*. Importantly, the yes/no question was worded in a way that reflected the skills used, whether involving staff or external contractors (See Table 9 in the Appendix for precise wording). Consequently, the focus of the question is more about the *use* of skills within the firm rather than the specific employment of staff with these skills (thereby including, for instance, the activities of freelance workers who are not permanent employees). In line with the STEM definition, we classify *software design*, *engineering*, and *mathematics* as STEM skills. Of these, engineering and maths are part of the STEM abbreviation, and we consider that software development, as phrased in the survey, to be nearer STEM than creative in this context. This is an important classification as software appears in some definitions of the creative industries (which could argue for classification as a creative skill). However, we take the view that computer science is generally considered to be a core STEM subject (by both the O*NET definition and HEFCE/DBIS 2016a, b) and classify it as such. We draw upon the UK's official definition of creative occupations (ibid) to identify *design*, *graphics* and *multimedia* as creative skills. Finally, we consider management skills. Management skills are particularly difficult to measure as they are fundamentally intangible, and overlap with managerial practices or activities, but not completely (O'Gorman et al. 2005). Consequently managerial efficacy, or managerial skills, are often proxied by the use of specific managerial practices (see for instance Haber and Reichel 2007; Srećković 2018), for instance the use or development of management skills, namely the introduction of new business practices for organising work procedures, or new methods of organising work responsibilities and decision making.

3.4 Variables

3.4.1 Dependent variable

The dependent variable of our regressions is turnover growth calculated as the difference of the logarithms of turnover: $ln(\text{Turnover}_{i, t}) - ln(\text{Turnover}_{i, t-1})$. All the variables used in our models are described in Table 2, while descriptive statistics and bivariate correlations of these variables are reported in Table 3.[5]

3.4.2 Independent variables

For the purposes of our analysis, we created three sets of dichotomous variables measuring the use of different types of skills by the firms in our sample. These sets of variables will be included in our model in different steps. First of all, we created a variable indicating whether firms used any skill at all (*ANY Skill*). Second, we considered any firm that responded positively to using at least one of the three creative skills (*design*, *graphics*, or *multimedia*) in the survey as using creative skills. We made a similar identification for STEM (*software design*, *engineering*, or *mathematics*) and management skills (*new business practices for organising work procedures*, or *new methods of organising work responsibilities and decision making*). This allowed us to create three variables: *CREAT Skills*, *STEM Skills* and *MGMT Skills*. These variables capture all firms that reported the use of these skills *tout court*, without considering the combinations in which they occurred. Third, we considered the combinations in which these skills occurred, by creating a number of non-overlapping dummy variables which capture both the individual use of these skills (*CREAT Only*, *STEM Only* and *MGMT Only*), and all their possible combinations (*CREAT & STEM*, *CREAT & MGMT*, *STEM & MGMT* and *CREAT, STEM & MGMT*). Specifically, *CREAT Only* refers to firms that only reported the use of creative skills but not STEM or management. Similarly, *STEM Only* and *MGMT Only* include firms that only used STEM or management skills, respectively. We then moved on to examine skill combinations, so *CREAT & STEM* includes firms that reported the use of both creative and STEM skills but not management skills. *CREAT & MGMT* and *STEM & MGMT* include firms that combine creative and STEM skills and STEM and management skills, respectively. Finally, *CREAT, STEM & MGMT* include those firms that reported the use of all three types of skills in the period.

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[5] We notice that none of the correlations appears to be particularly high. In addition to this, we also calculated the variance inflation factors for our independent variables, which are all below the threshold level of 5, providing no indication of strong multi-collinearity.

Table 2 Variable names, definitions and source

Variable	Definition	Source
Growth $_{i,t}$	Growth of turnover of firm i in period t: $ln(turnover_{i,t}) - ln(turnover_{i,t-1})$	BSD
Log turnover $_{i,t-1}$	Log of turnover of firm i in period $t-1$: $ln(turnover_{i,t-1})$	BSD
Log age $_{i,t-1}$	Log number of years since establishment of firm i in period $t-1$: $ln(age_{i,t-1})b$	BSD
R&D intensity $_{i,t-1}$	Ratio between R&D expenditure and turnover of firm i in period $t-1$: $R\&D_{i,t-1} / Turnover_{i,t-1}$	UKIS/ BSD
Capital investments $_{i,t-1}$	Ratio between investments in capital goods and turnover of firm i in period $t-1$: $Capital\ goods\ investments_{i,t-1} / Turnover_{i,t-1}$	UKIS/BSD
Human capital $_{i,t-1}$	Percentage of employees with a higher education degree of firm i in period $t-1$	UKIS/BSD
ANY Skill $_{i,t-1}$	Dummy indicating whether firm i reported any use of any type of skill in period $t-1$	UKIS
CREAT Skills $_{i,t-1}$	Dummy indicating whether firm i reported the use of creative skills in period $t-1$	UKIS
STEM Skills $_{i,t-1}$	Dummy indicating whether firm i reported the use of STEM skills in period $t-1$	UKIS
MGMT Skills $_{i,t-1}$	Dummy indicating whether firm i reported the use of management skills in period $t-1$	UKIS
CREAT Only $_{i,t-1}$	Dummy indicating whether firm i reported to only use creative skills in period $t-1$	UKIS
STEM Only $_{i,t-1}$	Dummy indicating whether firm i reported to only use STEM skills in period $t-1$	UKIS
MGMT Only $_{i,t-1}$	Dummy indicating whether firm i reported to only use management skills in period $t-1$	UKIS
CREAT & STEM $_{i,t-1}$	Dummy indicating whether firm i reported to use creative and STEM skills in period $t-1$	UKIS
CREAT & MGMT $_{i,t-1}$	Dummy indicating whether firm i reported to use creative and management skills in period $t-1$	UKIS
STEM & MGMT $_{i,t-1}$	Dummy indicating whether firm i reported to use STEM and management skills in period $t-1$	UKIS
CREAT, STEM & MGMT $_{i,t-1}$	Dummy indicating whether firm i reported to use all three types of skills in period $t-1$	UKIS

3.4.3 Control variables

Finally, we control for a number of variables which are often used in firm growth studies. First, we include a measure of firm size (*log turnover*) which is used to maintain our specification compatible with Gibrat's law approach (Calvo 2006; Stam 2010; Leoncini et al. 2017). Firm size is particularly relevant in the context of the diversity of knowledge used by firms. Indeed, there is substantial evidence that larger firms maintain, and indeed require, larger knowledge bases (Pavitt 1998; Brusoni et al. 2001). Smaller firms, with fewer resources, are more likely to specialise in particular areas that are amenable to specialisation (Pavitt 1984; Acs and Audretsch 1987). Entrepreneurial firms, drawing on diverse and diffuse knowledge and opportunities from the outside environment (Dew et al. 2004), may create value by recombining knowledge in novel ways (Galunic and Rodan 1998; Carnabuci and Operti 2013). Consequently, attention to firm size is required as this

could be a substantial explanatory factor behind the prevalence of combinations of skills.

We also control for Firm age (*log age*) (Heshmati 2001; Coad et al. 2016a, b), and *R&D Intensity* (R&D expenditure/turnover) (Capasso et al. 2015; Coad et al. 2016a, b). Finally, we include *capital investments* (capital goods investments/turnover) and *human capital* (share of employees holding a higher education degree), which have been often considered as able to influence the heterogeneity in growth patterns (Heshmati 2001; Andries and Czarnitzki 2014; Leoncini et al. 2017). Only in the case of pooled OLS regressions, we will also control for time invariant characteristics using sectoral (one-digit SIC levels) and regional dummies (Government Office Regions).[6]

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[6] The breakdown by sectors and regions is reported in Tables 10 and 11 in the Appendix.

Table 3 Descriptive statistics and correlation matrix

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Growth	0.060	0.568	1																
2. Log turnover	8.674	1.796	−0.101***	1															
3. R&D intensity	0.145	2.070	0.143***	−0.125***	1														
4. Capital investments	0.073	1.898	0.151***	−0.069***	0.576***	1													
5. Human capital	0.190	0.267	0.059***	0.021	0.14***	0.052***	1												
6. Log age	2.891	0.684	−0.109***	0.34***	−0.097***	−0.048***	−0.106***	1											
7. ANY skill	0.734	0.442	0.064***	0.19***	0.031***	0.02	0.238***	0.035***	1										
8. CREAT skills	0.507	0.500	0.042***	0.21***	0.016	0.019	0.185***	0.088***	0.611***	1									
9. STEM skills	0.514	0.500	0.041***	0.291***	0.055***	0.023	0.281***	0.078***	0.619***	0.484***	1								
10. MGMT skills	0.393	0.488	0.077***	0.038***	0.007	0.015	0.147***	−0.048***	0.485***	0.172***	0.207***	1							
11. CREAT only	0.079	0.270	−0.017	−0.052***	−0.02	−0.007	−0.065***	0.016	0.177***	0.289***	−0.302***	−0.236***	1						
12. STEM only	0.075	0.263	−0.017	0.031**	0.041***	−0.006	0.053***	0.004	0.172***	−0.289***	0.277***	−0.229***	−0.084***	1					
13. MGMT only	0.094	0.292	0.031***	−0.121***	−0.019	0.001	−0.071***	−0.088***	0.194***	−0.327***	−0.332***	−0.385***	−0.095***	−0.092***	1				
14. CREAT & STEM	0.186	0.389	−0.001	0.183***	0.012	0.012	0.095***	0.087***	0.288***	0.472***	0.465***	0.273***	−0.141***	−0.136***	−0.154***	1			
15. CREAT & MGMT	0.046	0.210	0.015	−0.057***	−0.013	−0.007	0.015	−0.009	0.133***	0.217***	−0.226***	0.307***	−0.065***	−0.063***	−0.071***	−0.105***	1		
16. STEM & MGMT	0.057	0.233	0.012	0.027**	0.002	0.001	0.084***	−0.017	0.149***	−0.25***	0.24***	0.612***	−0.073***	−0.07***	−0.08***	−0.118***	−0.054***	1	
17. CREAT, STEM & MGMT	0.195	0.396	0.057***	0.15***	0.029**	0.021	0.176***	0.02	0.297***	0.486***	0.479***		−0.145***	−0.14***	−0.159***	−0.236***	−0.108***	−0.122***	1

Correlation significance: * < 0.1; ** < 0.05; *** < 0.01

4 Results

As discussed above, our main research question asks whether use of STEM, creative and management skills and all their possible combinations are associated with a higher firm performance, measured by sales growth. We begin by presenting descriptive analysis to show which uses and combination of skills are the most prevalent in our sample. Our main econometric analysis takes the form of panel regressions with FE using different specifications and pooled OLS regressions.

4.1 Descriptive results

The descriptive results are presented in Tables 4 and 5. Table 4 shows the prevalence of the skills seen in the sample, regardless of the individual use or combination of these skills. Overall, 73.38% of the firms used at least one of the three types of skills considered in this study (creative, STEM and management) in the observation period. The use of different types of skills is quite balanced in the case of creative (50.72%) and STEM skills (51.40%), while management skills are less prevalent (39.32%), and 26.62% of firms did not report using any of the types of skills considered. However, these categories described the use of these skills *tout court*, without considering whether these skills are used individually or in combination with other skills. When we consider the range of possible skill combinations, we get a better picture of the distribution of these combinations. Table 5 shows the breakdown of firms by use of skills.

Among the firms that used some types of skills, 24.87% specialized in only one type of skills, 28.99% combined two skills and 19.52% used all three types of skills. Among the specialized firms, the most frequently used skills are the management ones (9.43%), followed by creative (7.94%) and STEM (7.50%). If we consider the firms combining two types of skills, 18.63% of firms used creative and STEM skills, while 4.62% used creative and management skills, and 5.74% STEM and management. Quite interestingly, the two most frequently combined skills are creative and STEM ones, by themselves (18.63%), or together with management skills (19.52%).

4.2 Multivariate results

Our main multivariate results are presented in Table 6, which is reporting the results of the panel FE

Table 4 Use of skills (individually or in combination with other skills) ($N = 6842$)

Skills	Percentage of firms
ANY skill	73.38%
No skills reported	26.62%
CREAT skills	50.72%
STEM skills	51.40%
MGMT skills	39.32%

regressions, and Table 7, which reports the results of pooled OLS. Model 1 represents our FE baseline results, including only the control variables. We note that most of the variables are associated with turnover growth. First, smaller firms in terms of turnover are more likely to experience a higher growth. The coefficients of *log age* and *log age squared*, both significant at the 10% level, appear to describe a U-shaped relationship between firm's age and growth.[7] Also R&D Intensity seems to have a nonlinear relationship with firm growth (inverted u-shape).[8] Finally, the coefficient of *capital investments* is positive and significant, while the one of *human capital* is not significant. These variables retain the same level of significance and about the same magnitude in models 2, 3 and 4 where the variables related with skills and skills combinations are added. These results are broadly consistent with the same regressions performed using pooled OLS (model 5), with the exception of *R&D intensity* and *capital investments* which are not significant in this case, and human capital which is significant at 10% level.

Model 2 tests whether using any type of skill (*ANY Skill*) without making any distinction between different kinds of skills is associated with sales growth, using an FE approach. The results show that this variable is positive and significant.[9] Similarly, *ANY Skill* is also positively and significantly associated with turnover growth also in the case of pooled OLS (model 6).

Model 3 adds the skill variables that include any use of any of the three skills considered (and not

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[7] The effect of *log age* has a minimum when age is about 4.8 years, which corresponds to the 5th percentile in the distribution of age in our sample. Formal investigation of the robustness of the U-shaped relationship (Haans et al. 2016) is beyond the scope of this paper.

[8] The effect of *R&D Intensity* has a peak at about 24%, which corresponds to the 86th percentile in the distribution in our sample.

[9] The coefficient of the variable *ANY Skill* is 0.133 which means that the use of any type of skill corresponds to an increase in the growth rate of approximately 13.3% with respect to the baseline category.

Table 5 Breakdown of firms by type of skills ($N = 6842$)

Skills		Percentage of firms
No skills reported		26.62%
Specialized in one type of skill: 24.87%	CREAT only	7.94%
	STEM only	7.50%
	MGMT only	9.43%
Combining two types of skills: 28.99%	CREAT & STEM	18.63%
	CREAT & MGMT	4.62%
	STEM & MGMT	5.74%
Combining all three skills: 19.52%	CREAT, STEM & MGMT	19.52%
Total		100.00%

their combinations). Here, we see that none of the skills is associated to a higher or lower growth. This seems to suggest that is not the use per se of these skills which may drive firm growth, but the specialization in one of these skills or the combinations of two or more of them. Quite interestingly, if we compare these results with model 7, which uses pooled OLS as method of estimation, we notice that in this case, all skills variables display positive and significant coefficients. This is an interesting result, which suggests that estimations of the impact of each of the skills on their own may be better explained by skills combinations when we use more robust panel analysis techniques.

The effects of a simultaneous or individual use of these skills are explored in model 4. In this model, we estimate the effect of all the possible specialization strategies (using only one type of skill) or combinations of skills on firm growth, with respect to the baseline category (i.e. firms which do not use any of the three types of skills considered). While the only specialization strategy with a significant coefficient is to use management skills only (*MGMT Only*), several skills combinations are associated with a higher firm growth. In particular, the combination of creative and STEM skills (*CREAT & STEM*), and of creative and management skills (*CREAT & MGMT*) is associated with a positive effect in terms of turnover growth. Finally, the firms combining all three skills (*CREAT, STEM & MGMT*) are more likely to report higher growth rates.

Specifically, the coefficient of the variable *CREAT & STEM* is 0.115, which means that the combination of creative and STEM skills corresponds to an increase in the growth rate of the firm of approximately 11.5% with respect to the baseline category. This increase in turnover growth is about 16.9% in the case of *CREAT & MGMT*, about 13.3% for *CREAT, STEM & MGMT*, and about 24.2% for *MGMT Only*. Although the effects related with investments in skills (and their combinations) presented above appear of a relevant magnitude, tests on differences among their regression coefficients show that there are no significant differences between them.

Model 8, based on pooled OLS regressions, provides very similar results. All the skills combinations that had an effect on turnover growth in the case of FE also do it in the case of pooled OLS (generally with higher level of significance), which also shows a significant and positive effect of *STEM & MGMT*.

Overall, these results seem to indicate that more than the mere use of skills is the combination of these skills which brings growth dividends to firms. With the exclusion of management skills that are also significant if used by themselves, several combinations of skills are associated with higher returns in terms of firm growth, including the simultaneous use of all three types of skills. Moreover, creative skills seem to play an important role, since they are not significant in if taken on their own, but they are always significant and with a positive effect on growth if they are combined with other skills.

4.3 Robustness checks

To further validate our findings, we carried out a number of robustness checks. First of all, we took into consideration the presence of size effects. The use of skills by the firms in our sample is measured using dichotomous variables, which are capturing the presence of skills and

Table 6 Results of the panel regressions with fixed effects

	(1)	(2)	(3)	(4)
ANY Skill $_{i,t-1}$		0.133**		
		(0.051)		
CREAT Skills $_{i,t-1}$			0.034	
			(0.042)	
STEM Skills $_{i,t-1}$			−0.004	
			(0.036)	
MGMT Skills $_{i,t-1}$			0.059	
			(0.041)	
CREAT Only $_{i,t-1}$				0.086
				(0.055)
STEM Only $_{i,t-1}$				0.101
				(0.078)
MGMT Only $_{i,t-1}$				0.242***
				(0.092)
CREAT & STEM $_{i,t-1}$				0.115**
				(0.056)
CREAT & MGMT $_{i,t-1}$				0.169*
				(0.092)
STEM & MGMT $_{i,t-1}$				0.067
				(0.087)
CREAT, STEM & MGMT $_{i,t-1}$				0.133**
				(0.063)
Log Turnover $_{i,t-1}$	−0.813***	−0.813***	−0.814***	−0.814***
	(0.080)	(0.079)	(0.079)	(0.079)
Log Age $_{i,t-1}$	−1.131*	−1.138*	−1.113*	−1.178**
	(0.619)	(0.606)	(0.610)	(0.594)
Log Age Squared $_{i,t-1}$	0.357*	0.368*	0.355*	0.385*
	(0.206)	(0.200)	(0.204)	(0.197)
R&D Intensity $_{i,t-1}$	0.149**	0.150**	0.147**	0.149**
	(0.067)	(0.067)	(0.067)	(0.065)
R&D Intensity Squared $_{i,t-1}$	−0.003*	−0.003*	−0.002*	−0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Capital Investments $_{i,t-1}$	0.110***	0.111***	0.110***	0.110***
	(0.015)	(0.015)	(0.015)	(0.014)
Human Capital $_{i,t-1}$	−0.060	−0.076	−0.059	−0.078
	(0.126)	(0.126)	(0.126)	(0.126)
Constant	7.426***	7.243***	7.357***	7.219**
	(0.889)	(0.885)	(0.884)	(0.871)
Firms	1267	1267	1267	1267
Observations	2759	2759	2759	2759
R^2	0.311	0.315	0.313	0.317

Dependent variable: *Growth* $_{i,t}$. Clustered standard errors in parentheses. Dummy for year periods have been included in all the models. The R^2 reported is the "within" R^2, from the mean-deviated regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Results of the pooled OLS regressions

	(5)	(6)	(7)	(8)
ANY Skill $_{i,t-1}$		0.082***		
		(0.016)		
CREAT Skills $_{i,t-1}$			0.030*	
			(0.015)	
STEM Skills $_{i,t-1}$			0.033**	
			(0.016)	
MGMT Skills $_{i,t-1}$			0.065***	
			(0.014)	
CREAT Only $_{i,t-1}$				0.030
				(0.022)
STEM Only $_{i,t-1}$				0.037
				(0.027)
MGMT Only $_{i,t-1}$				0.097***
				(0.026)
CREAT & STEM $_{i,t-1}$				0.079***
				(0.020)
CREAT & MGMT $_{i,t-1}$				0.087**
				(0.037)
STEM & MGMT $_{i,t-1}$				0.088**
				(0.037)
CREAT, STEM & MGMT $_{i,t-1}$				0.128***
				(0.023)
Log Turnover $_{i,t-1}$	−0.025***	−0.028***	−0.030***	−0.030***
	(0.005)	(0.005)	(0.005)	(0.005)
Log Age $_{i,t-1}$	−0.383***	−0.390***	−0.384***	−0.384***
	(0.091)	(0.091)	(0.090)	(0.090)
Log Age Squared $_{i,t-1}$	0.062***	0.064***	0.063***	0.063***
	(0.017)	(0.017)	(0.016)	(0.017)
R&D Intensity $_{i,t-1}$	0.012	0.010	0.009	0.009
	(0.043)	(0.043)	(0.043)	(0.043)
R&D Intensity Squared $_{i,t-1}$	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Capital Investments $_{i,t-1}$	0.031	0.031	0.031	0.031
	(0.023)	(0.022)	(0.022)	(0.022)
Human Capital $_{i,t-1}$	0.072*	0.042	0.033	0.034
	(0.037)	(0.037)	(0.037)	(0.037)
Constant	0.771***	0.763***	0.766***	0.764***
	(0.149)	(0.148)	(0.147)	(0.147)
Observations	6842	6842	6842	6842
R^2	0.053	0.057	0.059	0.059

Dependent variable: *Growth* $_{i,t}$. Clustered standard errors in parentheses. Dummy for year periods, regions and sectors have been included in all the models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

not their quantity. However, there is an argument which may suggest that the presence of positive returns from combining skills could be mainly derived by the role of large firms, which may be more likely to mix diverse types of skills simply because they are large. Therefore, further elaborating on our findings, we considered different size effects in Table 8, which presents the FE model with all skills combinations (model 4 in Table 6) run on three categories of firms grouped according to their size measured in terms of number of employees[10] (defined here as firms with between 10–49 employees; 50–249 employees and above 250 employees) to see if the effect identified above is limited to particular sizes of firms. The analysis of the first size group (10–49 employees) shows a significant effect for *MGMT Only*, *CREAT & STEM*, *CREAT & MGMT*, and *CREAT, STEM & MGMT*, mimicking the result of the regressions performed on the entire sample. Interestingly, the second size group (50–249 employees) find no significant effects at all. Finally, in the case of the third group of firms (with more than 250 employees), we also find some significant and positive effects, though here, we are considerably more cautious about the results, given the comparatively small sample size and low R2, which suggest that there are more unexplained sources of variation.

This suggests that the results of the regressions carried out on the entire sample presented in Table 6 do not seem to equally apply to all size categories of firms, but mainly to the case of small firms with less than 50 employees (though excluding the firms with less than 10 employees which are not included in the sample). One potential explanation for this finding is that small firms, given their size and limited amount of resources, find it difficult to diversify the skillsets of their employees, and therefore experience greater returns than other, larger firms.

While we deem that the FE estimation is the most appropriate for our analysis (further confirmed by the Hausman test), it could be argued that random effects could also be appropriate (see for instance the literature on the links between human resource practices and firm performance, e.g. Huselid and Becker 1998). On this basis, as a robustness check, we estimate random effects

models for our panel and present the results in Appendix Table 12. The results are consistent with our main findings.

There are a number of further robustness checks that we do not present for concision but are available upon request. As highlighted above, a potential issue associated with the use of UKIS data for panel analysis is that these data are not deliberately designed to be used as a panel. This means that only a fraction of our firms have surveyed in multiple waves of UKIS. In particular, for the purpose of this paper, in order to create a panel dataset, we included firms which appeared in two of three waves considered or more. This specific characteristics of UKIS data, plus the existence of missing values in the survey, reduced the number of observations-per-firm in our panel analysis. We addressed this problem by providing pooled OLS regressions (Table 7) along with the FE results. In addition to this, we have also made several further checks. First, we run the pooled OLS regressions including all the information available, i.e. even the firms that have participated in only one single survey wave. Then, we run separate OLS regressions on each of the three waves. Finally, we run our fixed effects panel regressions only considering the firms that appeared in all three waves. Our main results held across all these attempts.

We also tested whether the effects of skills combinations and turnover growth still hold if we shorten or lengthen the period in which the turnover growth is measured. We notice that if we measure, firm growth is measured on a shorter period of time (for instance, 2010–11 instead of 2010–12, in the case of regressors in the period 2008–10), we obtain consistent results with our main estimates. However, if you calculate growth on a longer period of time (e.g. 2010–13), we do not obtain significant results indicating that combining different types of skills produce benefits in terms of future turnover growth, but these effects tend not to persist over a too long period of time, suggesting a decaying effect.

Finally, we estimate a version of the model excluding firms that replied to the survey saying that they used all skills, as a means of avoiding potential response-style bias (i.e. firms answering 'yes' to all questions), but the results are again consistent.

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[10] Similarly, to firm turnover, the variable measuring the number of employees is based on official data from the BSD. Number of employees is calculated as the average number of employees in the 3-year period in which the other variables based on the UKIS were measured.

Table 8 Regressions for size categories

	10–49 employees (9)	50–249 employees (10)	250+ employees (11)
CREAT Only $_{i,t-1}$	0.148**	0.015	− 0.032
	(0.073)	(0.121)	(0.065)
STEM Only $_{i,t-1}$	0.159	− 0.063	0.102
	(0.137)	(0.110)	(0.070)
MGMT Only $_{i,t-1}$	0.198**	0.194	0.175
	(0.099)	(0.199)	(0.187)
CREAT & STEM $_{i,t-1}$	0.186**	0.072	0.001
	(0.086)	(0.106)	(0.072)
CREAT & MGMT $_{i,t-1}$	0.226**	− 0.032	0.337**
	(0.088)	(0.244)	(0.134)
STEM & MGMT $_{i,t-1}$	0.054	− 0.004	0.202*
	(0.145)	(0.123)	(0.103)
CREAT, STEM & MGMT $_{i,t-1}$	0.220**	0.071	0.005
	(0.097)	(0.116)	(0.064)
Log Turnover $_{i,t-1}$	− 0.722***	− 0.999***	− 0.721***
	(0.098)	(0.150)	(0.100)
Log Age $_{i,t-1}$	− 1.726	− 0.804	− 0.532
	(1.102)	(0.778)	(0.446)
Log Age Squared $_{i,t-1}$	0.555	0.314	0.203
	(0.369)	(0.285)	(0.239)
R&D Intensity $_{i,t-1}$	0.127**	0.237**	2.086*
	(0.064)	(0.101)	(1.217)
R&D Intensity Squared $_{i,t-1}$	− 0.002	− 0.008***	− 2.882**
	(0.001)	(0.002)	(1.378)
Capital Investments $_{i,t-1}$	0.093***	1.141***	− 0.188**
	(0.015)	(0.283)	(0.092)
Human Capital $_{i,t-1}$	− 0.046	− 0.313	− 0.218
	(0.166)	(0.207)	(0.199)
Constant	5.644***	8.824***	7.467***
	(0.885)	(1.986)	(1.662)
Firms	534	434	299
Observations	1141	939	679
R^2	0.442	0.336	0.257

Panel regression analysis with fixed effects. Dependent variable: Growth $_{i,t}$. Clustered standard errors in parentheses. Dummy for year periods have been included in all the models. The R^2 reported is the 'within' R^2, from the mean-deviated regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Discussion and conclusions

This paper explores the impact of the use of workforce skills on firm performance. Certain types of skills—particularly STEM (science, technology, engineering and mathematics) skills—have been recently emphasized as being drivers of economic growth (e.g. Atkinson and Mayo 2010; Winters 2014), while other research has, following Florida (2002), separately highlighted the importance of creative skills (defined here as skills associated

with creative occupations, as opposed to skills explicitly linked to creativity), and management skills and practices (Bloom and van Reenen 2007; Bloom et al. 2019). Extant research has mainly explored the role of these skills at the regional level, with only a few studies examining their impact—on their own and in combination—at the firm level. This paper represents an attempt to address this gap. Using panel and pooled cross-sectional data derived from the UK Innovation Survey and UK Business Structure Database, it explores the impact of the combination of STEM, creative and management skills on firms' future turnover growth.

Our results strongly point to the combination of skills as a factor contributing to firm growth. We find no evidence that STEM or creative skills, on their own, are associated with significantly higher levels of performance. We do, however, find that the benefits of both STEM and creative skills arise only when these skills are combined with another type, or types, of skill(s). This has a number of implications. First, management plays a crucial role in driving firms' turnover growth. Our results show that introduction of management skills in a firm that had previously not used these skills was associated with a subsequent 24.2% increase in turnover. This is congruent with the literature on the implementation of management practices[11] (e.g. Bloom and van Reenen 2007; Bloom et al. 2019). More importantly, we find that the benefits from STEM and creative skills only emerge in the presence of management skills, in the presence of each other (i.e. STEM and creative), or if all three types of skills are used. For instance, firms that combine STEM and management skills see an 11.5% increase in turnover, firms combining creative and management skills see a 16.9% increase and firms combining all three see a 13.3% increase in turnover. However, we found no statistically significant differences between these coefficients (that is, the skills combinations are significant, but no single combination has a coefficient that is significantly higher than the others). We therefore cannot conclude that the primary effect on turnover growth stems from the combination of two or more specific skills. The implication of this is that the specific mix of skills that has an impact on growth may vary depending on other

factors, such as firm's sector, type of activity or business model.

These findings are broadly consistent with the sizeable body of literature that points to the benefits of knowledge recombination (Fleming 2001; Yayavaram and Ahuja 2008; Stark 2011). However, whereas much of this literature focuses on the recombination of technological knowledge, we consider not just technological skills but also creative and management skills, and find that besides contributing to firms' innovation, these skill combinations generate positive effects on growth. Building on previously identified complementarities between creative and STEM skills for innovation (Sapsed et al. 2013; Siepel et al. 2016), we present a broadly Schumpeterian story in which innovations require managerial skills to be successfully exploited.

The contribution of our study is twofold. First, it is the first study, to our knowledge, to examine the impact of three distinct types of skills (STEM, creative and management) on firm performance. We show that while using cross-sectional techniques, we find a positive association between the use of STEM, creative and management skills individually and firm growth (supporting evidence provided by previous studies), when we adopt more robust estimation techniques, which better control for possible endogeneity issues; this positive association holds only for managements skills. Importantly, previous studies have found positive associations between STEM skills and growth, and creative skills and growth, but we find this effect is explained by the combination of each of these skills with other skills, rather than their presence on their own. The other positive findings for STEM and creative skills are better explained by skills combinations. This leads us to our second contribution, where we show that the benefits of both STEM and management skills are largely realised in combination with creative skills. This represents a novel and valuable finding that extends previous related work, which found a positive impact of STEM and creative skills (Brunow et al. 2018; Sapsed et al. 2013; Siepel et al. 2016,) and STEM and management skills (Siepel et al. 2017). By showing that superior performance is achieved by those firms that invest in skills combinations, we recognise the importance of the breadth of knowledge for firms, particularly smaller firms. Our findings hold for firms with between 10 and 49 employees, which suggests that investment in these skills among small firms is more likely to generate growth. It is likely that these smaller firms require a more diverse array of skills to be able to scale up.

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[11] This finding is intuitive, as a firm that has not utilised any skill is much more likely to make higher marginal efficiency gains by introducing new management practices, than is a firm that has already invested in some skills and decides to invest in more skills. In the latter case, the associated efficiency gains would be substantially smaller.

Some policy implications may also be drawn from our findings. In particular, our evidence provides a cautionary message to efforts to solely develop STEM skills at the expense of arts and humanities skills. Also, our findings challenge the received wisdom that there is a direct association between STEM skills and growth. We present a much more complicated picture that shows that the impact of STEM skills themselves is rather limited, but that it is through the *combination* with other types of skills that it unlocks growth. In so doing, our evidence supports the burgeoning global STEAM education movement, (adding an 'A' for Arts to the familiar STEM acronym). Our findings also hold across industries, thereby pointing to the importance of creative skills also for firms operating in sectors outside those traditionally associated with the 'creative milieu'. This adds further support to the view that policymakers should broaden their focus to creative activities in the wider 'creative economy'—not just in the creative industries—to fully capture the impact of creative skills throughout the economy.

As with all research, ours has some important limitations. We acknowledge that the relationship between skills and firm growth may be affected by endogeneity issues. While we tried to address this by using panel fixed-effects models and we tried to account for reverse causality and unobserved heterogeneity, experimental or instrumental variable techniques could provide better approximations of causality. It is worth emphasizing, however, that we do not make statements of causality in this paper but only point to associations among variables. Further limitations are in large part due to the nature of the data. The UKIS is not exclusively a longitudinal study so the panel element is limited, meaning that our preferred specification is an unbalanced panel. We have done our best to address these issues through the various robustness checks previously described. Moreover, given the structure of the data, we only know whether a firm used a skill but we are not able to capture the magnitude of this use, which prevents the identification of threshold effects whereby firm performance is affected. Finally, common to all studies based on survey data, measurement error is a further source of concern. We feel that this issue is not more important here than in other surveys, and the repeated and standardised nature of the UKIS (as part of the European Community Innovation Survey), which has been running biannually since the 1990s (see ONS 2017), gives us some

confidence. With this said, the risk of respondents' misunderstanding or misreporting is present.

This paper presents a number of avenues for future research. As previously highlighted, we refrain from explaining the effects that we observe as being truly causal. Studies able to identify means to address causality using other methods would be valuable. Moreover, valuable contributions could be provided by research exploring the interaction between different types and levels of skills, and from longitudinal studies investigating the performance implications of the accumulation of skills over time. Interesting findings could also come from the analysis of the use of internally developed skills versus externally acquired ones. The presence in the UKIS of questions asking about the use of skills accessed inside and outside the firm makes this a viable option. Future research could also examine what particular mix of skills is more beneficial depending on firm's characteristics, demography, sector of activity or business model. We hope that our core finding regarding the positive link between the combination of STEM, creative and management skills and firm performance provides the basis for future research into skills combination and firm performance.

Appendix

Table 9 Survey questions regarding skills

Variable	Questions	
Creative skills	During the 3 year period 1 January 20XX - 31 December 20XX, did your business employ individuals in-house with the following skills at any level, or obtain these skills from external sources:	Graphic arts/layout/advertising Design of objects or services Multimedia/web design
STEM Skills	During the 3 year period 1 January 20XX - 31 December 20XX, did your business employ individuals in-house with the following skills at any level, or obtain these skills from external sources:	Software development/database management Engineering/applied science Mathematics/statistics
Management skills	During the 3 year period 1 January 20XX - 31 December 20XX, did this business make major changes in the following areas?	New business practices for organising procedures (i.e. supply chain management, business re-engineering, knowledge management, lean production, quality management etc) New methods of organising work responsibilities and decision making (i.e. first use of a new system of employee responsibilities, team work, decentralisation, integration or de-integration of departments, education/training systems etc)

Source: UK Innovation Survey Questionnaire

Table 10 Breakdown by sector

Sector	Percentage
Agriculture, Forestry and Fishing	0.67%
Mining and Construction	6.75%
Manufacturing	22.01%
Transportation, Communications, Electric, gas and Sanitary Service	29.47%
Wholesale and Retail Trade	9.15%
Finance, Insurance and Real Estate	12.16%
Services	19.79%
Total	100.00%

Table 11 Breakdown by region

Region	Percentage
North East	3.73%
North West	10.13%
Yorkshire and The Humber	8.30%
East Midlands	7.83%
West Midlands	8.90%
Eastern	9.70%
London	11.77%
South East	14.16%
South West	7.97%
Wales	5.14%
Scotland	8.27%
Northern Ireland	4.09%
Total	100.00%

Table 12 Results of the panel regressions with Random Effects

	(12)	(13)	(14)	(15)
ANY Skill $_{i,t-1}$		0.082***		
		(0.015)		
CREAT Skills $_{i,t-1}$			0.030*	
			(0.015)	
STEM Skills $_{i,t-1}$			0.033**	
			(0.016)	
MGMT Skills $_{i,t-1}$			0.065***	
			(0.015)	
CREAT Only $_{i,t-1}$				0.030
				(0.021)
STEM Only $_{i,t-1}$				0.037
				(0.027)
MGMT Only $_{i,t-1}$				0.097***
				(0.026)
CREAT & STEM $_{i,t-1}$				0.079***
				(0.020)
CREAT & MGMT $_{i,t-1}$				0.087**
				(0.037)
STEM & MGMT $_{i,t-1}$				0.088**
				(0.037)
CREAT, STEM & MGMT $_{i,t-1}$				0.128***
				(0.023)
Log Turnover $_{i,t-1}$	− 0.025***	− 0.028***	− 0.030***	− 0.030***
	(0.005)	(0.005)	(0.005)	(0.005)
Log Age $_{i,t-1}$	− 0.383***	− 0.390***	− 0.384***	− 0.384***
	(0.089)	(0.089)	(0.088)	(0.089)
Log Age Squared $_{i,t-1}$	0.062***	0.064***	0.063***	0.063***
	(0.016)	(0.016)	(0.016)	(0.016)
R&D Intensity $_{i,t-1}$	0.012	0.010	0.009	0.009
	(0.045)	(0.045)	(0.045)	(0.045)
R&D Intensity Squared $_{i,t-1}$	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Capital Investments $_{i,t-1}$	0.031	0.031	0.031	0.031
	(0.023)	(0.023)	(0.023)	(0.023)
Human Capital $_{i,t-1}$	0.072**	0.042	0.033	0.034
	(0.037)	(0.036)	(0.037)	(0.037)
Constant	0.771***	0.763***	0.766***	0.764***
	(0.146)	(0.145)	(0.144)	(0.145)
Firms	5350	5350	5350	5350
Observations	6842	6842	6842	6842
R^2	0.129	0.139	0.135	0.138

Dependent variable: *Growth* $_{i,t}$. Clustered standard errors in parentheses. Dummy for year periods, regions and sectors have been included in all the models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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