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Top Team Demographics, Innovation and Business Performance: Findings from English Firms and Cities 2008-9

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Abstract
High levels of net migration to the UK have contributed to growing cultural diversity, and researchers are turning their attention to the long-term effects of diversity on productivity. Yet little is known about these issues. This paper asks: what are the links between the composition of firms' top teams and business performance? What role do ethnic diversity and co-ethnic networks play? And do cities amplify or dampen these channels? I explore using a rich dataset of over 6,000 English firms.

Owners, partners and directors set firms' strategic direction. Top team demography might generate production externalities through diversity (a wider range of ideas/ experiences, helping problem solving) and/or 'sameness' (via specialist knowledge or better access to international markets). These channels may be balanced by internal downsides (lower trust) and external barriers (discrimination), so that overall effects on business performance are unclear. In addition, urban locations (particularly big cities) may amplify any demographics-performance effects. I create a repeat cross-section of firms from the RDA National Business Survey. I construct measures of diversity and sameness across ethnicity and gender 'bases', alongside information on revenues, product and process innovation. I then regress these measures of business performance on top team demographics, plus firm level controls, area, year and detailed industry fixed effects.

My results suggest a non-linear link between diversity and business performance, which is net positive for process innovation and net negative for turnover. Further tests on diverse and minority/female-headed firms find positive links for diverse top teams, negative for minority and female-only top teams. This implies that while diversity has internal and external benefits, penalties from being 'too diverse' probably result from external constraints. Further tests for intervening effects of capital cities, metropolitan hierarchies and urban form find some evidence of amplifying and dampening effects – which are generally stronger in London and larger cities.

JEL Classifications: J61, L21, M13, O11, O31, R23
Keywords: Cities, innovation, entrepreneurship, cultural diversity, migration, gender

1. Introduction

This paper asks: what are the links between the demographic composition of senior staff in firms, and those firms' levels of innovation and revenues? What roles might ethnic and gender diversity have? Are minority- and female-headed firms at an advantage? I use a rich dataset of nearly 10,000 English firms to explore these issues.

These questions are important for both researchers and policymakers. The UK, like many other Western countries, has become substantially more ethnically and culturally diverse in recent decades, with net migration a main driver. The latest Census data make this very clear: between 2001 and 2011, the foreign-born population of England and Wales rose from 4.6 to 7.5m (from 9-13% of the population). At the same time, the share of 'white' and 'white British' ethnic groups decreased, drops of 91.3-86% and 87.5-80% respectively. Notably, the biggest-growing ethnic group was 'other white', with Polish-born the fastest-growing migrant group (Office of National Statistics, 2012b, Office of National Statistics, 2012a). These demographic changes have been most striking in urban areas: notably, London is now a ‘majority minority’ city for the first time in its history.

Given these long term shifts, attention is increasingly turning to the dynamic effects of immigrant communities on host country economies, particularly through firm-level channels that shape productivity, and through the diversity that migration brings (see Kerr and Kerr (2011) for a recent review). Gender equality and diversity are also major policy agendas in developed economies. In the UK, particular public attention is paid to the presence and impact of women in senior positions; and to encouraging female entrepreneurship (Davies Review, 2011).

Owners, partners and directors of firms – the ‘top team’ - help set the strategic direction of the businesses they run, and play an important role in their success or failure (Certo et al., 2006). In theory, there are two broad ways in which 'top team' demographic composition might affect business performance. One argument highlights externalities from diversity: specifically, a range of skills, knowledge, backgrounds and experiences may help teams to generate new ideas and to problem-solve (Page, 2007). Both gender and ethnic diversity could produce this advantageous mix. The other perspective emphasises gains from sameness - for example, externalities from social networks or deeper specialist knowledge, both of which may aid knowledge diffusion and market reach (Docquier and Rapoport, 2012).

Note that in theory both these channels have ambiguous effects - diverse teams may exhibit lower trust, social networks may be constrained, and minority or female-headed firms may experience discrimination. Thus the diversity-performance relationship may be non-linear, with an optimal level of mix after which disadvantages outweigh advantages (Ashraf and Galor, 2011). Note also that diversity and sameness channels are not mutually exclusive; both could run in parallel, and that different ‘diversities may’ have different effects. What empirical evidence exists suggests small net positive effects for ethnicity and gender on various measures of business performance, but there remain large knowledge gaps and problems identifying causal effects (Nathan, 2012, Adams et al., 2010, Certo et al., 2006).

In addition, cities or urban locations may amplify or dampen these processes – the former through agglomeration or composition effects, the latter through higher levels of competition, segregation or discrimination. These intervening factors are likely to be particularly salient for ethnic-diverse and minority ethnic headed businesses, but little quantitative work has been done in exploring their real effects (Nathan and Lee, Forthcoming).

I use rich microdata from the English Regional Development Agencies' National Business Survey to shed light on these issues. I pool data for 2008 and 2009 to create a sample of over 6,000 firms in England. I regress measures of top team diversity and sameness, by ethnic and gender, on measures of firms' product and process innovation activity, and on business revenue/turnover.

My results suggest a non-linear link between diversity and business performance, implying both positive and negative affordances. Echoing other studies, this translates to a small net positive term of ethnic diversity on levels of process innovation. More surprisingly, I find negative *net* relationships between ethnic and gender diversity and business turnover, implying that internal or external constraints ultimately outweigh benefits. I run further tests distinguishing diverse and minority/female-headed firms, here finding generally positive diversity-performance links but zero or negative links for minority and female-headed businesses. This suggests that while business diversity has (internal and external) benefits, being 'too diverse' is probably an issue of external constraints to the firm (such as discrimination) rather than internal problems. I also test for any amplifying effects of London, other large UK metros, and urban form generally. Here my results some evidence of amplifying and dampening effects, which are generally stronger and more visible through a London or 'city' lens than a broader urban / rural one.

The paper makes a number of contributions. First, while gender diversity and its role in 'top teams' has been previously explored in the empirical literature, the role of ethnic diversity and co-ethnic communities on business performance has been under-examined, especially in the 'top team' business context. Second, I look at different aspects of diversity together, and to explore their links to multiple business outcomes – not only product and process innovation, but resulting levels of business revenue. Third, I link the management literature (on top teams) to research on migration and diversity issues, and research by economists and geographers on the dynamic impacts of migration and migrant / minority communities, especially in urban environments. In so doing, the paper adds to the European literature on the 'economics of diversity' (Nathan, 2012). As far as I am aware, it is the first quantitative study of its kind in the UK, and provides a useful extension to recent research on diversity and innovation in London (Nathan and Lee, Forthcoming).

The paper is organised as follows. Section 2 builds a simple conceptual framework and reviews relevant empirics. Sections 3 and 4 describe the data and identification strategy respectively. Section 5 sets out the model and gives some brief descriptive analysis. Sections 6 and 7 describe the main results, with a tranche of robustness checks in Section 8. Section 9 discusses and sets out ideas for further research.

2. Framework and Evidence

2.1 Definitions

'Diversity' is hard to define in a form suitable for quantitative analysis. In this context, diversity refers to the mix of identity groups in a firm, or more precisely in the top team of owners/partners. Identity is a multifaceted concept, with subjective elements, and categories that alter over time (Aspinall, 2009). Gender and ethnicity are two important aspects of identity that I will use here. Gender diversity is defined in terms of female presence. Following the literature, I will treat ethnicity as given, not endogenous, and will largely abstract away self-ascribed elements (Ottaviano et al., 2007, Green 2011).[1] I also follow UK Office of National Statistics ethnic group definitions, which tend to focus on 'visible

[1] If identity is entirely self-ascribed, it becomes very hard to link behaviour to measures (Casey and Dustmann 2009). However, in practice it unlikely that (for example) commercial success might lead business owners of South Asian origin to identify as 'White British'.

minorities' and operate at a fairly high level of generality. Here, 'minority ethnic' refers to Black and Minority Ethnic (BME) groups.

I am interested in two main measures of business performance: innovation and turnover. I borrow the UK Government's definition of innovation as 'the successful exploitation of new ideas' (Department of Innovation Universities and Skills, 2008). Innovation thus involves both 'upstream' generation of new products and processes, and their 'downstream' commercialisation (Fagerberg, 2005).My data allows me to observe whether or not this 'upstream' product and process innovation has taken place. Turnover is defined as revenue: specifically, 'turnover' is the level of revenue that a firm receives from its normal business activities in a given time period.

The notion of a 'top team' is taken from the management literature, specifically the 'upper echelons' research pioneered by Hambrick and Mason (1984). The definition is deliberately broad to cover the 'dominant coalition' in a firm, comprising both senior directors (who may be employees) and owners and partners (Carpenter et al., 2004).

2.2 Framework

There are two main perspectives on how top team demographics may affect business performance. The first view emphasises the importance of diversity. Diverse firms and teams may benefit from a wider range of ideas, perspectives and backgrounds, which ought to improve problem-solving and ideas generation – and thus raise measures of innovation to the firm (Page, 2007, Berliant and Fujita, 2007). Diversity may also help firms to better handle complex external business environments (Williams and O'Reilly, 1998). In both cases, demographic structure should feed through into higher revenues. These effects may be particularly important in 'knowledge-intensive' settings (Fujita and Weber, 2003). Conversely, diverse firms/teams may face internal challenges – specifically, trust and bonding social capital may be lower than for homogenous groups (Alesina and Ferrara, 2005). And externally, such firms may face discrimination from customers or suppliers (for example, finance providers). Both of these forces will have a negative influence on innovation and revenues.

The second view focuses on dimensions of 'sameness'. In part, negative affordances of diversity are simply positive affordances of similarity. However, theory also suggests further externalities that benefit firms. For example, co-ethnic networks may reduce transactions costs and aid knowledge diffusion (Agrawal et al., 2008, Docquier and Rapoport, 2012). Identity group membership may aid market access either geographically, through diasporic communities, or in terms of product space – for example, female-headed firms probably have better market knowledge of products and services aimed at women and families (Javorcik et al., 2011, Foley and Kerr, 2011). These channels should aid innovation and revenue growth respectively, and may be particularly important under globalisation (Saxenian, 2006, Yeung, 2009). However, sameness may also have downsides. Within the firm, a lack of diversity may shut off sources of innovation stemming from unfamiliar perspectives or knowledge (Boschma, 2005); externally, minority-ethnic or female-headed businesses may experience discrimination, limiting the ability to commercialise innovations and constraining revenues (Zenou, 2011, Patacchini and Zenou, 2012).

This brief discussion raises a number of points. First, both diversity and 'sameness' in firms may influence business performance. Equally, both have pros and cons, so predicted effects are ambiguous. Second, diversity and sameness operate through both distinct and overlapping channels, so could be complements or substitutes. Third, the shape of the relationship to performance is unclear: for instance, given the pros and cons of diversity, the true diversity-performance relationship in a firm/team may be U-shaped rather than linear, so that an 'optimal' level of ethnic/gender diversity exists (Ashraf and Galor, 2011). Fourth, it is important to look at different identity bases in isolation. Different aspects of diversity / sameness, such as gender and ethnicity, might then be linked to different outcomes.

It is also important to consider how these channels may operate in different parts of the firm. The demographics of senior management and the wider workforce may have different effects on measures of business performance. In theory, 'top team' composition is likely to be highly important: senior managers set the overall direction of the business, take strategic decisions and tend to have the most experience and human capital. Beginning with a seminal paper by Hambrick and Mason (1984), a number of studies in the management literature have developed models of firms' 'upper echelons' or 'top management team' (TMT), where the size, structure and composition of senior management have important direct and indirect effects on business performance (see Certo et al (2006) and Carpenter et al (2004) for recent reviews, and Adams et al (2010) for a related and highly relevant discussion on corporate boards). TMT models highlight the critical role of team 'demographics' as observable proxies for behaviour: demographics are defined broadly to encompass age, gender, race/ethnicity, human capital, function, background and degrees of internal / external / international corporate experience. TMT models also highlight important 'intervening' factors both at firm level and in the wider business / social environment.

Spatial context provides a further dimension to explore. Specifically, cities or urban locations may amplify or dampen these processes – the former through agglomeration or composition effects, the latter through higher levels of competition, segregation or discrimination (Jacobs, 1969, Gordon et al., 2007, Berliant and Fujita, 2009, Goldin et al., 2011, Zenou, 2011). These intervening factors are likely to be particularly salient for ethnic-diverse and minority ethnic headed businesses, but little quantitative work has been done in exploring their real effects, especially in the UK (Nathan and Lee, Forthcoming).

Despite the richness of these frameworks, identifying *causal effects* of diversity / sameness on business performance presents a number of major challenges, which I briefly preview here. A first issue is to try and isolate team/group-level effects from individual characteristics, other firm-level characteristics and wider contextual factors deriving from industry, time trends, local area conditions or policy shocks. A second is the chance of simultaneity or causation at area level; successful firms may select into the largest markets, which *ceteris paribus* will tend to have larger and more diverse populations. A third issue, which is very hard to disentangle, is both-ways causation within the firm. Suppose there is a 'diversity bonus' of some kind which positively influences company performance; firms observe this and change their hiring patterns to suit. In practice, I am able to deal with the first and second issues through careful controls and fixed effects; future versions of the paper will use instruments to deal with the third. There is further discussion in Section 5 below.

2.3 Evidence base

The existing literature on these issues falls into two broad categories. Economists studying migration issues are increasingly trying to analyse links between migration, migrant communities and productivity – at individual, firm and area level. Many of these studies also look at second and third-generation communities, and more broadly at economic impacts of ethnic diversity.

A handful of these studies look specifically at diversity and business performance at the firm level, focussing on innovation outcomes. Ozgen et al (2011) find some positive links between migrant worker share, workforce diversity and innovation in knowledge-intensive Dutch firms. In Denmark, Parotta and colleagues (2011) find significant positive effects of cultural diversity on firms' propensity to innovate and on productivity – but again, only in 'white collar' sectors employing predominantly skilled workers. Lauren et al (2004), in a study of engineering consulting firms, find a curvilinear relationship between human capital diversity and business performance. Maré et al (2011, 2011) find no systematic links between workforce characteristics and innovation, but some productivity links, among businesses in New Zealand. In the UK, Nathan and Lee (forthcoming) find positive links between top team diversity and innovation in London firms.

A larger number of studies in look at diversity and market orientation (see Page (2007) for a recent review). For example, in a study of 165 Swiss firms, Nielsen finds that nationality mix in management teams is linked to higher rates of foreign market entry and greater profitability (cited in Hart (2010)). International evidence from economic geography also suggests that diasporas can engage in innovative activity. Saxenian (2006) and Saxenian and Sabel(2008) provide detailed evidence on the roles of migrant diasporas in Silicon Valley, which have strong links to production clusters in India, Taiwan and (increasingly) China. Similarly, Kapur and McHale (2005) and Kerr (2008) detail the roles of diasporas in the development of ICT clusters in Ireland, Israel and South East Asia. Dahlman (2010) shows how national Governments in BRIC (Brazil, Russia, India and China) countries have taken an increasingly active role here.

Notably few studies in this tradition attempt to look at multiple diversity bases, and very few focus on senior personnel. An exception to the former is a cross-sectional Danish survey by Ostergaard et al (2011), which finds no significant links between ethnicity and propensity to innovate, but a positive link between an 'open' firm culture and innovative performance, and a positive association between firms' gender diversity and the propensity to innovate.

In contrast, the strategic management literature has a long tradition of empirical 'TMT' research, and analysis on multiple aspects of workplace diversity. Carpenter et al (2004) and Certo et al (2006) provide useful reviews of the TMT literature and conduct meta-analyses. Both find that while there are typically modest effects of top team demographic factors on business performance, there are substantial intervening elements both at firm level and in the wider industry / spatial environment.

Individual studies in this tradition predominantly focus on teams' mix of age, education, function and background (see for example Buyl et al (2010), Naranjo-Gil et al (2008), Pitcher and Smith (2001), Wiersema and Bantel (1992), Bantel and Jackson (1989)). Jackson et al (2003) review the wider workplace diversity research: they note that while gender-based analyses are relatively common, ethnicity-based studies are much rarer, and there are very few studies which attempt to combine 'multi-dimensional diversity' in a way that reflects actual processes of self-ascription, e.g. 'Asian female scientist'.

A much smaller number of studies look at ethnicity and/or gender mix in top teams. For instance, Dezsö and Ross (2012) conduct a panel data analysis of the S&P top 1500 firms. They find that female representation in top management improves firm performance, but only when the firm has an 'innovation-focused strategy'. Asiedu et al (2012) look at US SMEs and access to finance, finding significant differences in loan approvals and interest rates between firms owned by white males and those owned by minority or white females. Francoeur et al (2008) suggest that firms operating in complex environments generate positive and significant abnormal returns when they have a high proportion of female senior managers. Dahlin et al (2005) find that national diversity in teams has a u-shaped relationship with information sharing and use.

3. Data

My main data source is the English Regional Development Agencies' National Business Survey (hence NBS), which was conducted in two waves every year from 2003 through to

2009 (the Agencies were formally abolished in 2011). Each wave covered around 5,000 firms across the nine English regions including London.[2] Data has been weighted by employee numbers and region, to reflect the national profile (Ipsos MORI, 2009). The NBS included questions about owner/partner ethnicity and gender in the Autumn waves of the 2008 and 2009 data, and these form the basis of my sample.

The NBS has many strengths. The UK has surprisingly few rich sources of firm-level data. The NBS is a single source that asks a detailed range of questions about business performance and constraints, as well as top team and firm characteristics. Importantly, the data allows me to separately identify diversity and sameness information along multiple dimensions, alongside multiple measures of business performance. The NBS also includes industry codes at up to four-digit level and detailed spatial identifiers for NUTS1-3 areas, enabling me to fit detailed sectoral and area fixed effects alongside firm-level controls. As such it is substantially more informative than other business-level datasets such as the ARD, and more comprehensive in its issue coverage than survey-based data such as the Community Innovation Survey or the Workplace Employer Response Survey.

However, there are also limitations to the data. It is a sample rather than a universe of firms, and information on ethnicity is only available for a couple of years. There is no panel structure to the data, so a repeat cross-section is the only feasible setup. In some areas of the survey the question format also varies significantly from year to year, so that constructing time-consistent variables loses some detail available in individual cross-sections. Finally, the NBS only contains information on top team demographics, rather than the wider workforce, and has no direct information on senior individuals or firms' wider human capital. To deal with this last issue, I draw on detailed small-area level human capital and occupational structure information from the Annual Population Survey (APS), which contains a boosted local sample which allows for reliable sub-regional estimates.[3] To enable better exploration of urban / city-level effects, I also add in Eurostat and ONS typologies of urban-rural form and metropolitan hierarchy (see section 7 for more details).

4. Identification Strategy

I use the NBS to explore links between measures of top team composition and measures of business performance. Specifically, I link firm-level variations in ethnic and gender team composition to variations in firms' turnover and innovative activity, while controlling for other firm, industry, area and time characteristics. I am particularly interested in 1) whether an increase in senior management diversity is linked to an improvement in business performance; 2) whether diversity and sameness are substitutes or complements, and the relative size and direction of their effects, and 3) which dimensions of diversity (sameness) matter, that is, the relative roles of ethnicity and gender as 'bases'.

I construct the sample by combining the 2008 and 2009 Wave 2 cross-sections. I restrict the analysis to firms for which there is information on innovative activity, turnover, industry and area, giving me a basic sample of 6,227 observations. Each observation

[2] The full list of regions is the North East, North West, Yorkshire and Humber, West Midlands, East Midlands, East of England, South East, London and the South West.

[3] The Annual Population Survey (APS) combines results from the English Labour Force Survey (LFS) and the English, Welsh and Scottish LFS boosts, and asks 155,000 households and 360,000 people per dataset about their own circumstances and experiences regarding a range of subjects including housing, employment and education. The APS' increased sample size provides substantially greater precision than the LFS when working at sub-regional level, as the analysis in this paper requires.

represents a single firm coded to one of 62 two-digit industry categories, geocoded to one of 107 NUTS3 areas and observed in a single year (2008 or 2009).[4]

4.1 Main variables

My independent variables of interest are measures of top team diversity and similarity, using ethnicity and gender bases. The NBS provides information on the ethnic and gender composition of firms' owners / partners / directors. I use this to build two types of variables covering diversity and sameness. First, I make continuous variables measuring a) the share of minority ethnic owner/partners in the firm, and the b) share of female owners/partners. These are my basic measures of diversity. I also construct c) quadratic terms to explore the potentially non-linear relationship between diversity and performance.

Next, I make a series of dummy variables for both ethnicity and gender, distinguishing firms with all majority ethnic (white British) owners/partners, and all-male owners/partners ('homogenous firms'), a mix ('diverse firms') and all minority ethnic / female owners/partners ('minority ethnic-headed' / 'female-headed' firms). This allows me to fit measures of diversity and sameness together, testing whether the two are complements and substitutes. More broadly, I am able to look at the degree of complementarity between ethnicity and gender bases.

My dependent variables are innovative activity and revenue / turnover, which are also well covered in the NBS. For innovative activity, I fit dummies taking the value 1 if the firm has, in the past 12 months, introduced 1) a new product innovation or 2) a new process innovation. These definitions are deliberately broad, as survey-based analyses need to capture very different innovation conditions across manufacturing and service sector firms.[5] Annual turnover information is provided in bands – eight bands in 2008, and four bands in 2009 (<£100k, £100-999k, £1-5m, >£5m). For the full regressions I fit a time-consistent four-band turnover variable; in robustness checks on the 2008 cross-section I use richer seven-band information.

4.2 Identification challenges

The data structure and sample construction three main identification challenges, which were introduced in Section 2 and discussed in detail here. The first, highlighted in the TMT literature, is that while I want to identify group-level characteristics of top teams on firm-level outcomes, I need to be able to isolate group-level characteristics from a) individual group member characteristics, such as human capital and entrepreneurial 'spirit'; b) other firm-level factors, such as age, size and previous investments; c) wider contextual factors such as location, time shocks, or industry trends (Certo et al., 2006, Carpenter et al., 2004). Each of a) - c) presents potential intervening factors which may affect both group demographics and business performance; for example, a technology shock might lower entry barriers in a given industry, enabling innovation and influencing top team composition as new firms form. Omitting these variables in regressions may lead to imprecision or worse, spurious correlations.

I am able to deal with most cases of b) and c) using careful control variables at firm level, as well as detailed industry, time and area fixed effects; I partially deal with a) by

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[4] I explore various cell configurations, covering SIC1-4 industry codes and NUTS1-3 area codes. My aim is to get the richest area and industry fixed effects without inducing measurement error through small cell sizes. In robustness checks I a) drop cells with NUTS2 and SIC3 frequencies under 10 b) use SIC1, NUTS2 and NUTS1 fixed effects with very little change to the main results.

[5] An inherent limit of this approach is that it risks capturing some trivial innovations, particularly in the process innovation category. Survey based methods may also risk a response bias towards innovating firms (Smith 2005).

fitting NUTS3-level human capital and occupational controls (see next section for more on these). Area-level factors present a second, related problem of positive selection. Innovative or high-turnover firms may choose to locate in the area with the greatest economic opportunities or innovation 'infrastructure', and this may vary by sector and firm type (Duranton and Puga, 2001). Not controlling for this means that coefficients of top team composition are likely to be biased upwards. The NBS structure does not identify moving firms, but this still leaves the possibility that historic location choices reflect persistent differences in local opportunities. I deal with this issue through area-level fixed effects that control for time-invariate area characteristics. I also exploit my choice of sample years: the UK was in recession in 2008-9 and the pull of successful areas will have been dampened during this time.

A third issue is simultaneity and/or reverse causation within the firm. If businesses observe a positive (negative) effect of top team composition on business performance, they may adjust team composition to maximise (minimise) any positive (negative) consequences for the firm (Ozgen et al., 2011, Parrotta et al., 2011, Nathan and Lee, Forthcoming). This will lead to at best, inflated coefficients of top team composition effects if not corrected, and at worst, spurious associations. This is an issue common to many studies in this field, and ideally, one would use a natural experiment that acted as a shifter of team composition to try and identify causal effects (Adams et al., 2010). A final issue also identified by Adams et al (ibid) is that, for a given company, exogenous firm-level heterogeneity may also influence the optimal top team composition *for that firm*. My controls strategy should deal with much of the observables, but the data structure does not permit firm fixed effects which would control for firm-level unobservables. For both reasons, I interpret results as associations rather than causal effects.

5. Estimation

I fit the data to a production-function type model, where for firm *i*, industry *j*, area *a* and year *t* I estimate:

$$Y_{ijat} = a + bETEAM_{ijat} + cFTEAM_{ijat}\ \mathbf{CONTROLS_{ijat}d} + J_j + A_a + T_t + e \qquad (1)$$

Y is variously a dummy for product or process innovation, or the firm's turnover. Both models relate measures of business performance to top team demographics (ETEAM, FTEAM), a vector of firm-level controls (CONTROLS) and fixed effects.

ETEAM covers top team characteristics by ethnicity. In the main results it is the share of minority ethnic owners/partners and its quadratic, which is my measure of diversity. Coefficients of ETEAM reflect the joint 'effect' of changes in ethnic composition on Y; as suggested above I am particularly interested in whether increases in diversity has a linear relationship with business performance, or whether an 'optimal' level of diversity exists. In extensions to the main analysis ETEAM includes dummies for minority ethnic-diverse and minority ethnic-headed firms. This specification enables me to explore the relationship between diversity and sameness: coefficients are 'effects' relative to being in a homogenous firm, the reference category. FTEAM is organised and interpreted along the same lines but for gender composition.

Controls are chosen to on the basis of the wider literature on business innovation and performance. Both firm age and firm size will influence the performance of the company: for instance, large or established firms often generate large amounts of patent activity, but small and/or new firms may introduce disruptive innovations (Griffith et al., 2006). Young, small firms also account for substantial shares of national output and employment growth (through rapid scaling) (Haltiwanger et al., 2010, Biosca et al., 2011, Lee, 2012). In turn, age and size may shape the composition of the firm's senior team. I therefore fit controls for the number of owners/partners, the age of the firm and the number of its employees. Company type is likely to influence both top team demographics and corporate performance; for example, subsidiaries and joint ventures of foreign-owned firms are more likely to benefit from knowledge spillovers and technology transfer (Aitken and Harrison, 1999, Javorcik, 2004, Harrison and Rodríguez-Clare, 2009). The NBS provides detailed information on company type, so I fit dummies for UK subsidiaries, foreign subsidiaries, ultimate holding companies, independents and LLPs (unknown status being the reference category). The NBS does not directly include information on firms' human capital stocks, but does ask about whether firms have attempted to improve their skills base through internal or external training; I use this as a proxy human capital control. I fit two controls for precision; namely dummies which take the value 1 if the firm has a codified growth plan, and if it is operating at capacity. Both should be positively correlated with innovation and with levels of revenue. Finally, J, A and T represent two-digit industry, NUTS3 and year fixed effects respectively.

A number of further controls are fitted in robustness checks. First, high-performing firms are more likely to export and work in international markets (Rodrik, 2004); supply chain and customer market geographies may also influence the make-up of firms' senior management. The NBS provides information on the share of inputs sourced domestically or abroad, and similar information for the pattern of sales, which are used to construct further controls. However, as only a limited number of firms answer these questions they are reserved for cross-checks.

Second, the 2008 NBS also provides information on a number of innovation related variables, which I fit in robustness checks on the cross-section. There is an established literature on 'open innovation' and collaboration, with firms that collaborate likely to access external knowledge and produce more innovations (Von Hippel, 2005). Other studies highlight the role of university-industry links (D'Este et al., 2011). Both of these should influence levels of innovation, and through this firm revenue. I therefore construct dummies for whether a firm uses specialist networks for information, and whether firms exploit university-industry links for R&D. I also include a dummy for whether the firm expects to invest in R&D during the year, reflecting the wide literature linking R&D and long-term business performance (Romer, 1990).

Estimators are chosen appropriate to the data structure. Innovation models are estimated as logistic regressions; following Angrist and Pischke (2009) I also show OLS results to indicate marginal effects. Turnover models are estimated as fixed effects OLS models.

5.1 Descriptives

Tables 1 and 2 provide some brief descriptive analysis. Table 1 gives summary statistics. The first panel covers my dependent variables: under a quarter of firms have introduced a product innovation, just under 10 percent a process innovation. Turnover is banded in four broad categories, and suggests the average firm has a turnover of around £100k. The second panel covers the main independent variables: the average share of minority ethnic owners/partners is around three percent; with 2.3 percent of firms being minority-ethnic headed. Female owner/partnership is much more common, the average firm having nearly 26 percent female owners/partners; female-headed firms comprise just under 10% of the sample. The third and fourth panels cover control variables. Controls in the fourth panel are used for robustness checks; some are only available for 2008.

Table 2 shows a correlation matrix for the main dependent, independent and control variables. Pairwise correlations are generally low, suggesting no inherent collinearity issues in the data.[6]

6. Main Results

Results for the main regression analysis are given in Tables 3-5 (innovation models) and 6 (turnover / revenue model). In each table column 1 fits a simple share of minority ethnic owners / partners; column 2 adds controls; column 3 fits the share and its quadratic; column 4 adds controls to this; column 5 adds the share of female owners and its quadratic. Innovation models are estimated in logit form, and point estimates are shown as raw coefficients. For these models Table 5 re-runs columns 3-5 in OLS to (roughly) illustrate marginal effects.

6.1 Innovation results

Product innovation results are given in Table 3. The model tests the links between the level of firms' share of top team minority ethnic and female owners/partners, and the likelihood that firm has introduced a product innovation in that year. The simplest specifications (columns 1 and 2) show no linear link. Including the share of minority ethnic owners/partners and its quadratic shows a small positive coefficient on the share, and a slightly smaller negative coefficient on the squared term. This is suggestive of a non-linear relationship where the joint effect is a small net positive – echoing the discussion in Section 2 – although neither is statistically significant. However, adding controls reduces coefficient size and – surprisingly - reverses their signs. The most fully specified model (column 6) fits shares and quadratics of both ETEAM and FTEAM. Coefficients of FTEAM are positive on the share (0.523, significant at 5%) and negative on the quadratic (-0.618, significant at 10%).

Table 4 switches attention to process innovation. As before, fitting the share of minority ethnic owners/partners shows no effect (columns 1 and 2), while fitting the share and its quadratic generates a robust and marginally significant relationship, where the joint effect is a small net positive (column 3). Interestingly, while the coefficients shrink as controls are added back in, ETEAM remains significant at 10%. Specifically, in the most fully specified model (column 6) the coefficient of the share of minority ethnic owners/partners is 1.937, significant at 10%, while the point estimate on the quadratic is -1.651. This suggests a positive link between diversity and process innovation, until a turning point is reached around a minority ethnic ownership share of about 0.3.

The left hand Table 5 shows the marginal effects for the product innovation model, which in for ETEAM is small and non-significant. For FTEAM, by contrast, both share and quadratic are significant – although as they exactly outweigh each other in the OLS, the overall marginal effect on product innovation is essentially zero (raw coefficients suggest a small net positive marginal effect).

The right hand panel shows the marginal effects for the process innovation model. For ETEAM, we can interpret this as showing that a 10 percentage point rise in the share of minority ethnic owners/partners is linked to a (0.203 + (-0.178*0.1) = 0.185 probability of a firm generating a process innovation. By contrast, coefficients of FTEAM remain insignificant and close to zero – although note that the square of the share of female owners/partners is (just) negative.

[6] Matrices for the full set of variables also suggest no collinearity. Results available on request.

6.2 Turnover results

Table 6 shows results for the turnover model. Unlike the innovation models, columns 1 and 2 find a small negative association between the share of minority ethnic owners / partners and turnover levels. Column 3 fits the share and its quadratic, and shows a large, strong positive linear link – but a slightly stronger negative link on the quadratic. Both coefficients are significant at 1%. Columns 4-6 add in controls. As expected, this shrinks the point estimates but the basic shape of the result survives. In column 6, the coefficient of the share of minority ethnic owners / partners is 0.730, significant at 5%, while its square is -0.798, significant at 1%.

This implies that a 10 percentage point rise in the share of minority ethnic owners/partners is linked to a (0.730 + (-0.798*0.1) = 0.068 unit fall in turnover. Note that this result controls for the age and size of the firm, company type and some measures of firm capacity, as well as industry, area and time fixed effects. Column 6 also adds FTEAM coefficients. Point estimates are substantially smaller than ETEAM, but again, the joint effect is a small net negative. In both cases this suggests a non-linear relationship between diversity bases and company performance, with a tipping point around an 'optimal' diversity level.

6.3 Diversity and sameness

The main results strongly suggest a non-linear relationship between top team diversity and business performance (and that gender and ethnic diversity play different roles). However, this leaves open the question of whether diversity and sameness act as complements or substitutes across the whole set of businesses. In order to explore this further, I run further regressions distinguishing between between diverse firms (with a mixed top team) and those headed by minority ethnic or female bosses. This allows me to look at whether diversity and 'sameness' are substitutes or complements *across the set of firms as a whole* – and whether different identity bases play out differently when re-cut this way.

In these models I fit dummies for ethnic / gender 'diverse' and minority ethnic/female 'headed' firms, with cofficients interpreted as relative effects of being X type of firm against being a 'homogenous' firm, the reference category. Descriptive analysis in Section 5 shows that a majority of firms are homogenous, with a minority of diverse firms and a much smaller group of minority ethnic and female-headed businesses.

Table 7 gives results for product innovation (left-hand panel) and process innovation (right hand panel). For product innovation, ethnic diversity has a negative coefficient and ethnic-headed status a positive coefficient, reflecting the relationship found in the previous results; neither is significant. Gender diversity has a positive link significant at 1%; female-headed firm status is also positive, but much smaller and non-significant. For process innovation, all coefficients of interest are positive but non-significant.

Table 8 gives results for the turnover model. Here, diversity measures have a strongly positive link to turnover, with measures of minority ethnic and female-headed firms showing negative linka. For example, the coefficient for ethnic diverse top teams is 0.165, significant at 1%, while the beta of minority-ethnic headed firms is -0.067. For gender, respective coefficients are 0.023 and -0.280 (1%).

7. Urban and Big City Location

Theory and evidence suggests that ethnicity-performance effects may influenced by large urban environments. Cities – and urban areas more generally – may amplify these channels (through demographic compositional effects or agglomeration economies) or dampen them (through greater competition or demographic segregation). Ethnic-diverse firms in cities/urban environments may therefore experience different outcomes from similar firms in smaller, less urban locations.

In the UK context these phenomena are perhaps most likely in London (Nathan and Lee, Forthcoming), but may also be present in other big cities and urban cores. Firm-level demographics and urban 'critical mass' may therefore interact in a way not captured by my existing control structure.

I am able to test for both city and urban effects. First, I code firms' locations using the Eurostat metropolitan hierarchy classification for NUTS3 areas, which sorts geographies into four categories: 'capital city region', 'second tier metro region', 'smaller metro region' and 'other regions'. Areas in these categories are coded respectively 4 through 1, so that larger scores indicate bigger city environments. Separately, I also fit a dummy for firms in London, which takes the value 1 if firm is in London NUTS2 area.

Next, I code firms' locations into a broader urban-rural typology. To do this I use two different classifications developed by Eurostat and the UK Office for National Statistics (ONS). The Eurostat typology has four categories: 'predominantly urban regions' (coded 4), 'intermediate regions, close to a city' (3), 'intermediate, remote regions' (2) and 'predominantly rural regions, close to a city' (1). The ONS typology has three broad groups, 'predominantly urban' (coded 3), 'significant rural' (2) and 'predominantly rural' (1).

I then fit interaction terms of firms' % minority ethnic owners/partners with metro code, the London dummy and the two urban/rural classifications. If London / big cities / urban areas amplify outcomes for firms, we should expect coefficients of interaction terms to be positive. If there is a dampening effect, interactions' point estimates will be negative.
Results are given in Table 9-11, for product innovation, process innovation and turnover respectively. In each case column 1 fits the base model, column 2 adds metro code and its interaction with the main variable; column 3 adds the London dummy, and columns 4-5 add the Eurostat and ONS urban-rural classifications. For innovation models, results are raw coefficients.

Product innovation results, shown in Table 9, generally show little significant differences from the base model (column 1). The coefficient of metro areas is negative, as is the interaction term – but this is small and close to zero. By contrast, diverse London firms have a greater likelihood of innovating compared to other diverse firms – but again, the effect is not significant. On both urban-rural classifications, the main coefficient of ETEAM turns positive (although with large standard errors), and the interaction term is negative (significant at 5% for the ONS classification).

Table 10 gives process innovation results. Perhaps surprisingly, bigger cities are associated with substantially less process innovation, as are diverse city firms – although the coefficient is around ten times smaller. Conversely, while firms in London are substantially and significantly more likely to innovate, diverse London firms are less likely to do so (although the link is not significant). More broadly, firms in more urban areas are linked to lower process innovation; but results for diverse urban firms vary across classification (negative and 5% significant for Eurostat, slightly positive for ONS).

Turnover models are given in Table 11, and as before, differ from the innovation results. City size and position is strongly linked to turnover, and diverse firms in bigger cities are linked to higher turnover (significant at 10%). Note that when the interaction term is fitted, the general (non-city) link from diversity to turnover drops and becomes non-significant. While there is also a positive London-turnover link, however, the diverse firm*London term has a small negative (non-significant) coefficient. Both urban-rural classifications indicate a positive link between diverse urban firms and higher turnover – but neither is significant, and the ONS coefficient is close to zero. When the Eurostat classification is fitted, the non-urban diversity-turnover link becomes non-significant.

Overall, I find some evidence of amplifying and dampening effects, which are generally stronger and more visible through a London or 'city' lens than a broader urban / rural one. For diverse firms, London has a (weak) positive link to product innovation, but a negative link to process innovation and turnover levels. This suggests that agglomeration, competition and discrimination effects may play out differently for different economic processes. Bigger cities as a whole may dampen innovation for diverse firms, but have a significantly positive link to levels of turnover. Urban area-diversity connections are significantly conditioned by the type of classification used.

8. Robustness Checks

I run a series of checks to test for potential specification and endogeneity issues.

First, I add in a number of innovation-related controls and re-run (1) for product and process innovation, using the 2008 cross-section. As discussed in Section 4, the 2008 NBS contains information on whether firms are planning to invest in R&D; whether they use university-industry links for R&D purposes; and whether they use specialist networks to obtain information. The innovation literature suggests all three will have a positive effect on innovative activity; networking and U-I activity may also influence, and be influenced by top team composition. Results are given in Table 12. In each case column 1 fits the pooled sample, column 2 the 2008 cross-section and column 3 cross section plus additional controls.

For product innovation, coefficients of ETEAM change sign, so that the share is positive and quadratic negative. Significant effects of FTEAM drop away in the cross-section, with and without additional controls. For process innovation, positive effects of ETEAM remain in the cross-section, but disappear once additional controls are added. There is little change for FTEAM, although the sign of the quadratic changes to negative. This suggests that the innovation results are conditioned by the additional elements included here.

Next, I re-run the turnover models including innovation variables on the right hand side. Intuitively, successfully commercialised innovative activity should feed through into greater market share, and thus higher revenue. Table 13 shows the results. Point estimates for both ETEAM and FTEAM change slightly, but the overall pattern of the main results stays unchanged.

As a further check on the turnover models, I refit the model for 2008 data using more detailed seven-band turnover information. The rich information on the left hand side of the model might reduce or amplify the observed diversity effects. The results are given in table 14: column 1 fits the pooled sample, column 2 the 2008 data and column 3 the 2008 data with seven-band turnover. Fitting the more detailed turnover information does not change the overall shape of significance levels of the results, although coefficients for individual variables of interest get bigger.

Following this, I re-run all the main models including right-hand side controls for inputs and sales geographies. As discussed in Section 5, both variables may shape firms' innovative capacity, business performance and the composition of senior management; not including them in (1) may omit an important intervening variable. Table 15 presents results including these controls. The top panel shows results for product innovation. For ETEAM and FTEAM there is little change.

The middle panel shows selected results for process innovation. Only a couple of the logit models converge, suggesting that the loss of observations is critical in these cases. (Results for OLS models, available on request, suggest that fitting both controls together shrinks the coefficient of ethnic-diverse firms, and renders it insignificant (from 10% significance); by contrast, the beta of minority-headed firms switches from positive to negative, and becomes marginally significant. Coefficients of FTEAM are essentially unchanged.

The bottom panel shows results for turnover. Here, including input and sales controls amplifies the main results. For ETEAM, fitting both new controls together raises the coefficient of ethnic diversity firms from 0.165 to 0.218; for FTEAM, the negative coefficient of female-headed firms switches from -0.280 to -0.325. In both cases results remain 1% significant.

Next I explore whether small and young firms shape the results in ways not captured by my existing control structure. The literature suggests that such firms play a critical role in employment growth; and this may well affect turnover as well (Haltiwanger et al., 2010). We might also expect small, young firms which are diverse or minority/female headed to display distinctive trajectories – depending on whether positive or negative demographic externalities predominate. To test this, I build two 'small and young' dummies taking the value 1 if firms are both less than 5 years old and a) are small businesses, with 10-50 employees, or b) are microbusinesses, with under 10 employees.

Results for innovation models show very little difference to the main findings (full tables are available on request). The one shift is for process innovation: when the microbusiness dummy is interacted with ethnic diverse teams, the coefficient of the latter rises from 0384 to 0.438, significant at 10%. Coefficients of microbusinesses and diverse microbusinesses are slightly negative, likely reflecting constraints on very small firms.

Table 16 presents results for the turnover models. Being a young small business has no significant link to turnover (column 2); not surprisingly, being a microbusiness attracts a substantial penalty (column 4). Columns 3 and 5 interact these dummies with the ethnic-diverse top team dummy. I find a weak negative link to turnover for small, young ethnic diverse firms (column 3) and for microbusinesses (column 5) but neither is significant.

Finally, I repeat the main results adding in NUTS3-level workforce composition controls, drawn from the Annual Population Survey for England and Wales. Specifically, I fit sequentially the a) share of directors, managers and senior officials employed in the NUTS3 working-age population, which functions as a measure of the pool of TMT personnel; b) a measure of workforce skills, the share of NUTS3 working-age population with degree-level qualifications; and c) the share of degree holders / senior and management employees. These are designed both to provide additional area-level information, and to proxy for the firm-level human capital information not present in the NBS. As such they are less precise than one would wish, and some coefficients are fitted quite imprecisely. The APS does not cover Northern Ireland: these firms are dropped from the checks.

Results are given in Table 17. The top panel shows results for product innovation; there is little change when the extra controls are fitted. The middle panel shows results for process innovation; fitting the area-level skills control slightly raises the beta of ethnic diverse firms (from 0.384 to 0.415) and makes it significant at 10%. The bottom panel fits turnover models. Here, coefficients of ethnic diverse teams get larger but also shift from 5 to 10% significance; the beta of minority ethnic-headed firms also gets large and becomes marginally significant. As with the other two dependent variables, there is very little change to measures of FTEAM.

9. Discussion

This paper explores the connections between top team ethnic and gender composition, innovation and revenue levels at the firm level, using a rich dataset of English firms. The paper makes a number of contributions to the small, but growing literature on dynamic effects of diversity, co-ethnicity and gender composition on business performance. It is one of very few firm-level European studies, and is (as far as I am aware) the first of its kind in the UK.

The early results throw up four headline findings. First, I find evidence that suggests a non-linear relationship link between ethnic and gender diversity and measures of business performance. This is in line with theory and some existing empirical evidence.

Second, the sign and strength of the link differs across outcomes. For innovation models, there is a strong and robust link between ethnic div and process innovation, though none for product innovation. Joint effect is small net positive, suggesting that positive affordances of diversity on innovation (ideas pooling, knowledge spillovers) outweigh any negatives (lower trust and social capital, discrimination). I find no links for gender diversity. For turnover models, I find strong, significant joint effects for both ethnic and gender diversity, the former larger than the latter. However, in contrast with the innovation results, both links are small net negative, suggesting that internal / external demographic constraints outweigh any positives.

Third, distinguishing between diverse and minority/female-headed businesses is important to explain these results. For process innovation, I find positive links to ethnically diverse firms but none to minority-headed firms. For turnover, I find positive to ethnic and gender-diverse firms, but negative links to minority and female-headed businesses. This suggests that while business diversity has (internal and external) benefits, being 'too diverse' is actually an issue of external constraints to the firm (such as discrimination) rather than internal problems.

Finally, in line with theory I find some evidence that city and urban form have amplifying / dampening effects on diversity-business performance links. These intervening effects are all fairly weak, reflecting the relatively broad-brush approach to spatial classification. A larger sample with post-code data for firms would allow much more precise estimates of city and urban effects, and future research could usefully explore this approach.

Extensions and robustness checks suggest two further channels that may be influencing these results, particularly for turnover models. These are first, the geography of inputs and sales; and second, specific constraints for small, young businesses. As expected, including controls on firms' R&D and networking activity also helps explain the main results.

The persistence of the main results suggests robust associations between top team demographics, process innovation and levels of turnover. However, at this stage these results cannot be interpreted as causal – because I cannot observe firms' reactions to any diversity or sameness 'effects'. In general, identifying causal effects of firm composition is beset with challenges, not least because similar firms are likely adopt heterogeneous strategies to deal with identical management issues (Adams et al., 2010). As Adams et al (ibid) point out, 'there are no cure-all instruments that one can use to deal with this endogeneity … causality, in the usual sense, is often impossible to determine.' (p 97).

Further research could pursue a number of different avenues. First, and most crucially for UK businesses and policymakers, future studies need to use instruments or other identification techniques that can identify causal effects of diversity and sameness on firm-level outcomes as far as possible. Second, differences between top team and wider workforce demographics-performance channels need better exploration, ideally through large, rich employer-employee datasets. Third, as noted above, better geo-coded data would allow clearer identification of city and urban-level intervening factors. Working with large public datasets and matching across microdata, or pursuing 'big data' strategies are both promising ways forward.

Tables

Table 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
new product innovation in last 12 months	6235	0.239	0.426	0	1
new process innovation in last 12 months	6235	0.088	0.284	0	1
turnover at site in 4 bands	6235	2.039	0.832	1	4
% minority ethnic owners/partners/directors	6235	0.030	0.159	0	1
(% minority ethnic owners/partners/directors)^2	6235	0.026	0.151	0	1
minority ethnic-diverse firm	6235	0.018	0.132	0	1
minority ethnic-headed firm	6235	0.023	0.149	0	1
% female owners/partners/directors	6235	0.259	0.332	0	1
(% female owners/partners/directors)^2	6235	0.177	0.296	0	1
minority female-diverse firm	6235	0.346	0.476	0	1
minority female-headed firm	6235	0.099	0.298	0	1
number of owners/partners/directors	6227	2.1	3.6	1	100
no of employees who receive a salary (excl. owners)	6235	25.9	374.9	0	20000
years business in operation	6226	3.478	0.807	1	4
firm is subsidiary of uk parent	6235	0.028	0.166	0	1
firm is subsidiary of foreign parent	6235	0.015	0.123	0	1
firm is ultimate holding company	6235	0.042	0.200	0	1
firm is independent	6235	0.688	0.463	0	1
firm is LLP	6235	0.077	0.267	0	1
business provided some training in past 12 months	6235	0.281	0.450	0	1
growth plan dummy	6051	0.333	0.471	0	1
business is operating below capacity	6235	0.684	0.465	0	1
share of foreign sales banded	5421	3.245	2.726	0	6
share of foreign inputs banded	6235	4.044	2.592	0	6
firm expects to do R&D investment in next 12 months	2894	0.621	0.485	0	1
business uses U-I links for R&D	1734	0.196	0.397	0	1
business uses specialist networks for info	2169	0.416	0.493	0	1

Source: RDA NBS.
Note: ownership truncated to 100 owners / firm.

Table 2. Correlation matrix of main variables

	prodin	procin	turnover	ethownsh	eth~h_sq	eth_div	eth_head	femownsh	fem~h_sq	fem_div	fem_head
new product innovation in last 12 months	1										
new process innovation in last 12 months	-0.1744	1									
turnover at site in 4 bands	0.1251	0.0729	1								
% ethnic owners/partners/directors	0.0066	0.0142	-0.0278	1							
(% ethnic owners/partners/directors)^2	0.0042	0.0097	-0.0364	0.9828	1						
minority ethnic-diverse firm	0.0135	0.0227	0.0464	0.318	0.1429	1					
minority ethnic-headed firm	0.0002	0.0055	-0.0421	0.9331	0.9822	-0.0205	1				
% female owners/partners/directors	0.0042	0.0179	-0.1663	0.0164	0.0152	0.0131	0.0144	1			
(% female owners/partners/directors)^2	-0.0051	0.0167	-0.1955	0.0133	0.0167	-0.0125	0.0197	0.9398	1		
female-diverse firm	0.0294	0.0136	0.0467	0.0118	-0.0012	0.0793	-0.0115	0.4505	0.1224	1	
female-headed firm	-0.0099	0.0107	-0.187	0.0071	0.015	-0.0402	0.0216	0.7391	0.9185	-0.2405	1

Source: RDA NBS.
Note: Obs = 6235. Correlation matrices for main variables and full controls are available on request.

Table 3. Product innovation. Logistic models

	(1)	(2)	(3)	(4)	(5)
% ethnic owners/partners/directors	0.103	0.060	0.538	-0.366	-0.545
	(0.189)	(0.226)	(0.695)	(0.779)	(0.763)
ethownsh_sq			-0.465	0.455	0.639
			(0.661)	(0.765)	(0.753)
% female owners/partners/directors					0.623**
					(0.256)
femownsh_sq					-0.618*
					(0.319)
number of owners/partners/directors		0.009		0.009	0.008
		(0.007)		(0.007)	(0.007)
no of employees who receive a salary (excluding owners)		0.000		0.000	0.000
		(0.000)		(0.000)	(0.000)
years business in operation		-0.068		-0.067	-0.071
		(0.049)		(0.049)	(0.048)
firm is subsidiary of uk parent		0.438**		0.440**	0.463**
		(0.183)		(0.182)	(0.180)
firm is subsidiary of foreign parent		0.568**		0.567**	0.610**
		(0.265)		(0.266)	(0.268)
firm is ultimate holding company		0.363**		0.363**	0.370**
		(0.159)		(0.159)	(0.161)
firm is independent		0.116*		0.116*	0.122*
		(0.070)		(0.071)	(0.072)
firm is LLP		0.192		0.193	0.194
		(0.140)		(0.141)	(0.141)
business provided some training in past 12 months		0.248***		0.248***	0.245***
		(0.057)		(0.057)	(0.057)
growth plan dummy		0.809***		0.810***	0.808***
		(0.094)		(0.095)	(0.097)
business is operating below capacity		0.111		0.110	0.112
		(0.072)		(0.072)	(0.072)
Observations	6203	5885	6203	5885	5885
Log-likelihood	-3144.216	-2893.196	-3144.125	-2893.121	-2890.859

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. Raw coefficients. HAC standard errors clustered on 2-digit sector. Constant not shown. * = result significant at 10%, ** = 5%, *** = 1%.

Table 4. Process innovation. Logistic models

	(1)	(2)	(3)	(4)	(5)
% ethnic owners/partners/directors	0.365*	0.408*	1.901*	1.923*	1.937*
	(0.200)	(0.220)	(1.048)	(1.103)	(1.106)
ethownsh_sq			-1.656	-1.637	-1.651
			(1.115)	(1.178)	(1.181)
% female owners/partners/directors					0.030
					(0.308)
femownsh_sq					0.205
					(0.338)
number of owners/partners/directors		0.008		0.007	0.007
		(0.005)		(0.005)	(0.005)
no of employees who receive a salary (excluding owners)		0.000		0.000	0.000
		(0.000)		(0.000)	(0.000)
years business in operation		-0.032		-0.034	-0.024
		(0.069)		(0.069)	(0.072)
firm is subsidiary of uk parent		0.326		0.319	0.326
		(0.257)		(0.258)	(0.256)
firm is subsidiary of foreign parent		-0.059		-0.052	-0.022
		(0.381)		(0.382)	(0.388)
firm is ultimate holding company		-0.016		-0.017	0.003
		(0.197)		(0.196)	(0.196)
firm is independent		0.085		0.084	0.088
		(0.138)		(0.137)	(0.137)
firm is LLP		0.268		0.264	0.277
		(0.267)		(0.266)	(0.267)
business provided some training in past 12 months		0.387***		0.388***	0.387***
		(0.108)		(0.109)	(0.109)
growth plan dummy		0.825***		0.822***	0.826***
		(0.107)		(0.107)	(0.106)
business is operating below capacity		-0.083		-0.082	-0.074
		(0.083)		(0.083)	(0.082)
Observations	6139	5831	6139	5831	5831
Log-likelihood	-1759.031	-1627.992	-1758.332	-1627.354	-1626.345

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. Raw coefficients. HAC standard errors clustered on 2-digit sector. Constant not shown. * = result significant at 10%, ** = 5%, *** = 1%.

Table 5. Innovation models. OLS results

	Product innovation			Process innovation		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
% ethnic owners/partners/directors	0.095	-0.071	-0.098	0.193	0.201	0.203
	(0.130)	(0.135)	(0.131)	(0.130)	(0.140)	(0.140)
ethownsh_sq	-0.086	0.084	0.111	-0.173	-0.177	-0.178
	(0.123)	(0.135)	(0.131)	(0.134)	(0.143)	(0.144)
% female owners/partners/directors			0.096**			0.006
			(0.040)			(0.024)
femownsh_sq			-0.096*			0.012
			(0.051)			(0.028)
Controls	N	Y	Y	N	Y	Y
Observations	6235	5922	5922	6235	5922	5922
r2	0.088	0.122	0.122	0.034	0.057	0.057

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown.
* = significant at 10%, ** = 5%, *** = 1%.

Table 6. Turnover model. OLS results

	(1)	(2)	(3)	(4)	(5)
% ethnic owners/partners/directors	-0.110	-0.011	1.002***	0.863***	0.730**
	(0.070)	(0.052)	(0.365)	(0.300)	(0.307)
ethownsh_sq			-1.186***	-0.931***	-0.798***
			(0.354)	(0.293)	(0.296)
% female owners/partners/directors					0.285***
					(0.090)
femownsh_sq					-0.602***
					(0.083)
number of owners/partners/directors		0.012***		0.012***	0.011***
		(0.004)		(0.004)	(0.004)
no of employees who receive a salary (excluding owners)		0.000***		0.000***	0.000***
		(0.000)		(0.000)	(0.000)
years business in operation		0.232***		0.232***	0.217***
		(0.017)		(0.017)	(0.018)
firm is subsidiary of uk parent		0.383***		0.380***	0.386***
		(0.088)		(0.086)	(0.087)
firm is subsidiary of foreign parent		0.830***		0.834***	0.819***
		(0.092)		(0.092)	(0.092)
firm is ultimate holding company		0.311***		0.311***	0.292***
		(0.059)		(0.058)	(0.059)
firm is independent		0.029		0.029	0.028
		(0.029)		(0.029)	(0.028)
firm is LLP		0.184***		0.183***	0.168***
		(0.034)		(0.034)	(0.036)
business provided some training in past 12 months		0.492***		0.492***	0.492***
		(0.028)		(0.028)	(0.027)
growth plan dummy		0.301***		0.300***	0.296***
		(0.022)		(0.022)	(0.022)
business is operating below capacity		-0.051**		-0.051**	-0.059***
		(0.018)		(0.018)	(0.018)
Observations	6235	5922	6235	5922	5922
r2	0.136	0.365	0.138	0.366	0.378

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. HAC standard errors clustered on 2-digit sector. Constant not shown. * = result significant at 10%, ** = 5%, *** = 1%.

Table 7. Product and process innovation. Testing diversity and sameness

	Product innovation		Process innovation	
	LOGIT	**OLS**	**LOGIT**	**OLS**
minority ethnic-diverse firm	-0.083 (0.184)	-0.016 (0.032)	0.384 (0.234)	0.039 (0.028)
minority ethnic-headed firm	0.076 (0.218)	0.010 (0.037)	0.284 (0.260)	0.025 (0.021)
female-diverse firm	0.165*** (0.059)	0.025*** (0.009)	0.078 (0.092)	0.006 (0.007)
female-headed firm	0.030 (0.108)	0.004 (0.018)	0.214 (0.204)	0.015 (0.018)
Controls	Y	Y	Y	Y
Observations	5885	5922	5831	5922
Log-likelihood	-2890.568	-2981.168	-1626.971	-829.346
r2		0.122		0.057

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. Raw coefficients. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 8. Turnover. Testing diversity and sameness

	(1)
minority ethnic-diverse firm	0.165** (0.076)
minority ethnic-headed firm	-0.067 (0.051)
female-diverse firm	0.023 (0.024)
female-headed firm	-0.280*** (0.026)
Controls	Y
Observations	5922
r2	0.376

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 9. Big city, London and urban area checks. Product innovation

	(1)	(2)	(3)	(4)	(5)
% minority ethnic owners /partners/directors	-0.545 (0.763)	-0.446 (0.787)	-0.575 (0.760)	1.640 (2.348)	0.747 (1.031)
ethownsh_sq	0.639 (0.753)	0.648 (0.757)	0.563 (0.747)	0.607 (0.753)	0.732 (0.802)
Eurostat metro classification (1-4, 4 = big metro)		-0.903 (0.724)			
% minority ethnic top team X Eurostat metro classification		-0.038 (0.134)			
London firm dummy			1.143 (0.744)		
% minority ethnic top team X London firm dummy			0.353 (0.314)		
Eurostat urban/rural classification (1-4, 4 = urban)				-0.301 (0.241)	
% minority ethnic top team X Eurostat urban/rural classification				-0.565 (0.564)	
ONS urban/rural classification (1-3, 3 = urban)					-0.590 (0.364)
% minority ethnic top team X ONS urban/rural classification					-0.539** (0.249)
FTEAM	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Observations	5885	5885	5885	5885	5623
Log-likelihood	-2890.859	-2890.839	-2890.576	-2890.250	-2792.104

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. Raw coefficients. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 10. Big city, London and urban area checks. Process innovation

	(1)	(2)	(3)	(4)	(5)
% minority ethnic owners /partners/directors	1.937* (1.106)	2.682** (1.223)	2.014* (1.094)	4.378** (1.794)	1.443 (1.446)
ethownsh_sq	-1.651 (1.181)	-1.536 (1.168)	-1.460 (1.224)	-1.684 (1.217)	-1.191 (1.122)
Eurostat metro classification (1-4, 4 = big metro)		-13.803*** (0.619)			
% minority ethnic top team X Eurostat metro classification		-0.311 (0.209)			
London firm dummy			14.009*** (0.411)		
% minority ethnic top team X London firm dummy			-1.008 (0.635)		
Eurostat urban/rural classification (1-4, 4 = urban)				-4.601*** (0.269)	
% minority ethnic top team X Eurostat urban/rural classification				-0.635** (0.304)	
ONS urban/rural classification (1-3, 3 = urban)					-7.094*** (0.336)
% minority ethnic top team X ONS urban/rural classification					0.022 (0.320)
FTEAM	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Observations	5831	5831	5831	5831	5566
Log-likeilihood	-1626.345	-1625.642	-1625.282	-1625.876	-1550.642

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. Raw coefficients. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 11. Big city, London and urban area checks. Turnover

	(1)	(2)	(3)	(4)	(5)
% minority ethnic owners /partners/directors	0.730**	0.524	0.744**	0.242	0.768**
	(0.307)	(0.337)	(0.312)	(0.525)	(0.345)
ethownsh_sq	-0.798***	-0.824***	-0.776**	-0.793***	-0.875***
	(0.296)	(0.294)	(0.291)	(0.297)	(0.295)
Eurostat metro classification (1-4, 4 = big metro)		0.321***			
		(0.115)			
% minority ethnic top team X Eurostat metro classification		0.083*			
		(0.049)			
London firm dummy			0.252		
			(0.206)		
% minority ethnic top team X London firm dummy			-0.146		
			(0.183)		
Eurostat urban/rural classification (1-4, 4 = urban)				-0.101	
				(0.162)	
% minority ethnic top team X Eurostat urban/rural classification				0.126	
				(0.123)	
ONS urban/rural classification (1-3, 3 = urban)					-0.022
					(0.108)
% minority ethnic top team X ONS urban/rural classification					0.015
					(0.057)
FTEAM	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Observations	5922	5922	5922	5922	5655
R2	0.378	0.378	0.378	0.378	0.378

Source: RDA NBS. All models use year, sic2 and nuts3 dummies. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 12. Innovation models: extra variables

Product innovation	**(1)**	**(2)**	**(3)**
% minority ethnic owners/partners/directors	-0.545	-0.508	0.370
	(0.763)	(1.659)	(2.540)
ethownsh_sq	0.639	-0.170	-1.037
	(0.753)	(1.636)	(2.359)
% female owners/partners/directors	0.623**	0.192	0.003
	(0.256)	(0.456)	(0.655)
femownsh_sq	-0.618*	-0.438	-0.064
	(0.319)	(0.517)	(0.724)
Standard controls	Y	Y	Y
Further controls	N	N	Y
Observations	5885	2798	1425
Log-likelihood	-2890.859	-1139.105	-616.872

Process innovation	**(1)**	**(2)**	**(3)**
% minority ethnic owners/partners/directors	1.937*	4.439**	3.558
	(1.106)	(2.253)	(2.497)
ethownsh_sq	-1.651	-3.973*	-3.676
	(1.181)	(2.251)	(2.453)
% female owners/partners/directors	0.030	0.461	0.934
	(0.308)	(0.584)	(0.719)
femownsh_sq	0.205	-0.346	-0.769
	(0.338)	(0.661)	(0.764)
Standard controls	Y	Y	Y
Further controls	N	N	Y
Observations	5831	2489	1162
Log-likelihood	-1626.345	-663.748	-380.412

Source: RDA NBS. All models use year, sic2 and nuts3 dummies, plus controls as in Tables 3 and 4. Raw coefficients. HAC standard errors clustered on 2-digit sector. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 13. Turnover models including innovation

	(1)	(2)	(3)	(4)
minority ethnic-diverse firm	0.165**	0.166**	0.163**	0.163**
	(0.076)	(0.076)	(0.076)	(0.076)
minority ethnic-headed firm	-0.067	-0.068	-0.069	-0.070
	(0.051)	(0.052)	(0.051)	(0.051)
female-diverse firm	0.023	0.022	0.023	0.021
	(0.024)	(0.024)	(0.024)	(0.024)
female-headed firm	-0.280***	-0.280***	-0.281***	-0.281***
	(0.026)	(0.026)	(0.026)	(0.026)
new product innovation in last 12 months		0.069***		0.083***
		(0.026)		(0.030)
new process innovation in last 12 months			0.060	0.086
			(0.053)	(0.058)
Observations	5922	5922	5922	5922
r2	0.376	0.377	0.376	0.378

Source: RDA NBS. All models use year, empl, sic2 and nuts3 dummies. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 14. Turnover models, seven band turnover

	(1)	(2)	(3)
minority ethnic-diverse firm	0.165**	0.170*	0.357*
	(0.076)	(0.094)	(0.197)
minority ethnic-headed firm	-0.067	-0.028	-0.165
	(0.051)	(0.087)	(0.178)
female-diverse firm	0.023	0.055**	0.096**
	(0.024)	(0.027)	(0.048)
female-headed firm	-0.280***	-0.281***	-0.591***
	(0.026)	(0.036)	(0.077)
Controls	Y	Y	Y
Observations	5922	2860	2860
r2	0.376	0.406	0.426

Source: RDA NBS. All models use year, empl, sic2 and nuts3 dummies. HAC standard errors clustered on 2-digit sector. Controls as in Tables 3 and 4. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 15. Foreign inputs and sales

Product innovation	(1)	(2)	(3)	(4)
minority ethnic-diverse firm	-0.083	-0.357	0.003	-0.362
	(0.184)	(0.330)	(0.182)	(0.330)
minority ethnic-headed firm	0.076	-0.380	0.158	-0.387
	(0.218)	(0.406)	(0.255)	(0.460)
female-diverse firm	0.165***	0.157***	0.162***	0.154***
	(0.059)	(0.059)	(0.057)	(0.057)
female-headed firm	0.030	0.031	0.077	0.107
	(0.108)	(0.161)	(0.128)	(0.165)
Share foreign sales	N	Y	N	Y
Share foreign inputs	N	N	Y	Y
Observations	5885	2464	5129	2315
Log-likelihood	-2890.568	-1156.777	-2620.193	-1084.907

Process innovation	(1)	(2)
minority ethnic-diverse firm	0.384	0.297
	(0.234)	(0.257)
minority ethnic-headed firm	0.284	0.023
	(0.260)	(0.295)
female-diverse firm	0.078	0.104
	(0.092)	(0.100)
female-headed firm	0.214	0.187
	(0.204)	(0.231)
Share foreign inputs	N	Y
Observations	5831	5067
Log-likelihood	-1626.971	-1457.035

Turnover	(1)	(2)	(3)	(4)
minority ethnic-diverse firm	0.165**	0.238***	0.183**	0.218**
	(0.076)	(0.088)	(0.073)	(0.083)
minority ethnic-headed firm	-0.067	-0.032	-0.080	-0.025
	(0.051)	(0.089)	(0.048)	(0.097)
female-diverse firm	0.023	0.025	0.011	0.020
	(0.024)	(0.033)	(0.024)	(0.034)
female-headed firm	-0.280***	-0.327***	-0.291***	-0.333***
	(0.026)	(0.049)	(0.027)	(0.052)
Share foreign inputs	N	Y	N	Y
Share foreign sales	N	N	Y	Y
Observations	5922	2523	5165	2368
r2	0.376	0.441	0.379	0.446

Source: RDA NBS. All models use year, sic2 and nuts3 dummies, plus controls as in Tables 3 and 4. Panels 1 and 2 fit raw coefficients. HAC standard errors clustered on 2-digit sector. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 16. Small and young firms: turnover models

	(1)	(2)	(3)	(4)	(5)
minority ethnic-diverse firm	0.165**	0.166**	0.173*	0.163**	0.171**
	(0.076)	(0.076)	(0.088)	(0.075)	(0.085)
minority ethnic-headed firm	-0.067	-0.068	-0.068	-0.064	-0.064
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
sysmall		0.045	0.045		
		(0.059)	(0.060)		
eth_sysmall			-0.050		
			(0.159)		
symicro				-0.148***	-0.147***
				(0.042)	(0.044)
eth_symicro					-0.067
					(0.170)
FTEAM	Y	Y	Y	Y	Y
Observations	5922	5922	5922	5922	5922
r2	0.376	0.376	0.376	0.377	0.377

Source: RDA NBS. All models use year, sic4 and nuts3 dummies, plus controls as in Tables 3 and 4. HAC standard errors clustered on 4-digit sector. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Table 17. Area-level workforce data. Innovation and turnover models

Product innovation	**(1)**	**(2)**	**(3)**	**(4)**
minority ethnic-diverse firm	-0.083	-0.193	-0.195	-0.191
	(0.184)	(0.247)	(0.255)	(0.248)
minority ethnic-headed firm	0.076	0.171	0.172	0.173
	(0.218)	(0.206)	(0.205)	(0.206)
female-diverse firm	0.165***	0.182***	0.182***	0.182***
	(0.059)	(0.068)	(0.068)	(0.068)
female-headed firm	0.030	0.040	0.042	0.040
	(0.108)	(0.096)	(0.098)	(0.097)
% all in employment		0.046		
managers directors and senior officials		(0.060)		
% working age population			-0.005	
with NVQ4 or above			(0.059)	
managers as share of NVQ4+ working				2.170
age population				(2.060)
Controls	Y	Y	Y	Y
Observations	5885	4999	4999	4999
Log-likelihood	-2890.568	-2484.279	-2484.687	-2484.002

Process innovation	**(1)**	**(2)**	**(3)**	**(4)**
minority ethnic-diverse firm	0.384	0.403*	0.415*	0.401
	(0.234)	(0.245)	(0.249)	(0.245)
minority ethnic-headed firm	0.284	0.132	0.131	0.131
	(0.260)	(0.277)	(0.280)	(0.277)
female-diverse firm	0.078	0.162	0.160	0.162
	(0.092)	(0.100)	(0.100)	(0.100)
female-headed firm	0.214	0.272	0.272	0.271
	(0.204)	(0.193)	(0.194)	(0.192)
% all in employment		-0.049		
managers directors and senior officials		(0.060)		
% working age population			-0.081	
with NVQ4 or above			(0.072)	
managers as share of NVQ4+ working				-1.521
age population				(2.077)
Controls	Y	Y	Y	Y
Observations	5831	4951	4951	4951
Log-likelihood	-1626.971	-1353.561	-1353.267	-1353.628

Source: RDA NBS. Raw coefficients. All models use year, sic2 and nuts3 dummies, plus controls as in Tables 3 and 4. HAC standard errors clustered on 2-digit sector. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

Turnover	**(1)**	**(2)**	**(3)**	**(4)**
minority ethnic-diverse firm	0.165**	0.173*	0.172*	0.172*
	(0.076)	(0.092)	(0.092)	(0.092)
minority ethnic-headed firm	-0.067	-0.100*	-0.100*	-0.101*
	(0.051)	(0.052)	(0.052)	(0.052)
female-diverse firm	0.023	0.012	0.012	0.012
	(0.024)	(0.025)	(0.025)	(0.025)
female-headed firm	-0.280***	-0.282***	-0.283***	-0.282***
	(0.026)	(0.029)	(0.029)	(0.029)
% all in employment		-0.012		
managers directors and senior officials		(0.011)		
% working age population			0.004	
with NVQ4 or above			(0.014)	
managers as share of NVQ4+ working				-0.551
age population				(0.358)
Controls	Y	Y	Y	Y
Observations	5922	5035	5035	5035
Log-likelihood	0.376	0.370	0.370	0.370

Source: RDA NBS. All models use year, sic2 and nuts3 dummies, plus controls as in Tables 3 and 4. HAC standard errors clustered on 2-digit sector. Constant not shown. * = significant at 10%, ** = 5%, *** = 1%.

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