ETHNIC DIVERSITY AND BUSINESS PERFORMANCE: WHICH FIRMS? WHICH CITIES?

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Abstract

A growing literature examines how ethnic diversity influences economic outcomes in cities and inside firms. However, firm-city interactions remain more or less unexplored. Ethnic diversity may help firm performance by introducing a wider range of ideas, improving scrutiny, or improving international market access. Urban locations may amplify in-firm processes via agglomeration economies, externalities from urban demography or both. These firm-city effects may be more beneficial for knowledge-intensive firms, and for young firms with a greater dependence on their environment. However, firm-city interactions could be negative for cost and competition-sensitive younger firms, or for firms operating in poorer, segregated urban markets. I deploy English cross-sectional data to explore these issues within firms' 'top teams', using latent class analysis to tackle firm-level heterogeneity. I find positive diversity-performance links for larger, knowledge-intensive firms, and positive firm-city interactions for larger, knowledge-intensive firms in London and for younger, smaller firms in second tier metros.

Keywords: cities, ethnic diversity, diversity, firm-level analysis, business performance

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1. Introduction

Researchers have become increasingly interested in the 'economics of diversity'. This reflects deep real-world demographic shifts: many Western countries have seen growing ethnic/cultural, with immigration one of the main drivers of change (Putnam, 2007). Much of this new diversity is urbanised, with 'super-diversity' is emerging in some neighbourhoods (Vertovec, 2007). Most strikingly, as non 'White British' populations grow, London has now become a 'majority minority' city for the first time in its history (Office of National Statistics, 2012).

Such shifts have triggered extensive popular debate about whether more cosmopolitan societies are economically or socially desirable (Florida, 2002; Gilroy, 2004), or whether ethnic/cultural diversity has costs (Collier, 2013; Goodhart, 2013). Within economics, geography and urban research, as the labour market impacts of migration become better understood, researchers are turning their attention to the wider implications of more ethnically diverse workforces and communities. The seminal work of Ottaviano and Peri (2005; 2006) led to a wave of studies exploring area-level diversity and urban economic outcomes (Lewis and Peri, 2015). A second wave of research has used firm-level data to explore transmission channels in detail, linking migrant and ethnic diversity to innovation, task specialisation, productivity, entrepreneurship and trade (Mannix and Neale, 2005; Nathan, 2014).

To date very few studies have combined firm and city-level perspectives. In this paper, I explore firm-level ethnic diversity-performance links, and how external conditions across urban locations can affect these. Within the firm, I focus on the composition of the 'top management team', senior staff who should play a major role in determining company success or failure (Hambrick and Mason, 1984). I use rich data on a cross-section of 2,300 English firms alongside area-level data, and deploy Finite Mixture Modelling to explore how firm-level processes and firm-city interactions differ across groups of businesses and city types.

This flexible approach helps to untangle a web of possible impacts. Theory and evidence suggest that ethnic diversity can affect firm outcomes as a prism for cognitive diversity, as a source of identity/norms, or both. If workforce ethnic diversity allows firms a larger pool of ideas, linkages and experiences, it can help in ideas generation or problem solving, improve assignment of workers to tasks, enable scrutiny, or facilitate access to new markets. However, diverse teams may suffer communication problems or a lack of trust; further, biases and social norms may lead others to discriminate against diverse or minority-led businesses. Urban locations may amplify such in-firm processes, via agglomeration economies, externalities from urban demography or both. Firm-city channels may be more beneficial for knowledge-intensive firms, and for young firms with a greater dependence on their external environment. However, the overall effect of diversity-performance channels is ambiguous, and firm-city interactions could also be negative, particularly for younger firms that are cost and competition-sensitive, or for firms operating in poorer, segregated urban markets.

I find small, positive ethnic diversity-performance connections across all firms, and suggestive evidence that these may be non-linear. However, mixture modelling suggests that these results are driven by a minority of larger, high-turnover, knowledge-intensive firms concentrated in Greater London and some large conurbations. For the majority of firms, links are non-significant and coefficients close to zero. Echoing German and US evidence on migrant diversity, I also find evidence of firm-city interactions for about 20% of the sample, which vary across locations and firm type. For large, high-turnover, knowledge-intensive firms a London location appears to amplify top team diversity-performance links; for younger, smaller, less knowledge-based firms, other large cities appear to benefit diverse firms more than London. The capital's higher costs, more competitive markets and poorer inner urban neighbourhoods, or a lack of 'nursery city' externalities for this group of firms may explain this result.

The paper is organised as follows. Section 2 sets out a simple framework and reviews relevant empirics. Section 3 introduces the data. Sections 4 and 5, respectively, cover identification and estimation issues. Section 6 gives results for the pooled sample, while Section 7 segments the data into homogenous groups. Section 8 concludes.

2. Framework

Ethnicity is a complex concept that includes not just visible appearance, but also aspects of culture, such as religion, nationality and identity (Aspinall, 2009). Ethnicity categorisation has evolved over time (Putnam, 2007). A range of theories suggests that ethnicity can affect preferences and outcomes, both as a basis for identity and as a cultural resource, and that organisations are important sites for this. Hofstede (1990; 1991) sees culture as a form of shared understanding, or 'software of the mind', which shapes the way families, organisations and countries develop. Organisational cultures are partially explained by individuals' cultural characteristics such as age, gender, class, or ethnicity, and these can feed through into hiring decisions (Rivera, 2012). Similarly, Haldane (2016) shows how societies and organisations exhibit deeply-rooted same-group membership dynamics, and that ethnicity is one way in which groups divide up. Akerlof and Kranton (2010) suggest that identity, the sense of social self, influences norms, the sense of how we and others should behave given our identities. They develop an 'identity economics' framework in which actors derive utility from conforming to norms – in families, organisations and neighbourhoods – and may maximise 'identity utility' over material gain.

A growing body of theory and empirical work examines whether ethnic/cultural *diversity* within organisations might influence firm performance. One perspective is that ethnic diversity can proxy for cognitive diversity, representing a range of backgrounds, ideas and experiences (Page, 2007). As such, more diverse workforces may improve problem-solving and ideas generation (de Vaan et al., 2015), allow for better task-substitution (Peri and Sparber, 2011), or both. These uplifts improve firm productivity and thus revenues. Ethnically diverse groups may also find it harder to communicate and trust each other, a drag on productivity (Mannix and Neale, 2005; Alesina and Ferrara, 2005). However, in some settings ethnic homogeneity may also be a bad, if trust leads to a lack of scrutiny or avoidance of disagreement (Phillips and Apfelbaum, 2013; Levine et al., 2014).

Another view is that ethnic diversity may help firms better access international markets, via individuals' connections or local knowledge (Docquier and Rapoport, 2012).[1] Conversely, diverse firms may also face discrimination from customers or suppliers, directly harming revenues. Even if discrimination is economically irrational, cognitive biases and/or social norms may guide actors to sub-optimal decisions (Akerlof and Kranton, 2010; Kahnemann, 2011).

We can add three layers to this basic framework. First, the demographics of the 'top management team' (TMT) in a firm (Hambrick and Mason, 1984) should be especially important: owners, partners and senior managers set the overall direction of the business, take strategic decisions and tend to have the most experience and human capital (see Certo et al (2006) and Carpenter et al (2004) for reviews). Second, diversity-performance links could vary in importance across sectors. Any gains from team diversity should be larger for firms in so-called 'knowledge intensive' manufacturing and service activities, where problem-solving and innovation is central to the production function (Mannix and Neale, 2005; Berliant and Fujita, 2012).

Third, urban characteristics may interact with these in-firm processes, although the net effect is again ambiguous, and partially determined by firm sector, size and age. If within-firm ethnic diversity is a production complementarity, agglomeration economies (knowledge spillovers, thick labour markets) may amplify its firm-level effects. Urban demography may also act as an externality – say if city-level diversity helps innovation in firms (via a larger ideas pool) or

[1] A closely related literature focuses on co-ethnic groups and diasporic communities, where social capital and networks may help in sharing information and facilitating trade. Docquier and Rapoport (2012) review this field.

improves labour market choice (making it easier to hire diverse teams). Ethnically diverse cities additionally present large, diverse local markets to sell into – an important consumption economy (Glaeser et al., 2001) – and within-firm diversity may help in accessing these (Buck et al., 2002). Such firm-city interactions should therefore be particularly important for young firms, for whom large cities can act as 'nurseries' (Duranton and Puga, 2001). Knowledge-intensive companies are strongly attracted to post-industrial cities for similar reasons (Hall, 2000; Scott, 2014).

On the other hand, diseconomies of agglomeration (more competitive markets, higher costs) may act as a dampener on urban firms (Ottaviano and Peri, 2006). Ethnic segregation in cities may limit diverse firms' potential to trade outside specific locations (Helsley and Zenou, 2014); similarly, income disparities and poverty within specific communities may also act as a drag on firm revenues and growth. Such urban disadvantages will be particularly germane to smaller, younger firms who will be most sensitive to cost and competition.

A large body of empirical studies of workforce ethnic diversity suggest ambiguous links to firm performance, reflecting the complexity discussed above (Williams and O'Reilly, 1998; Herring, 2009).[2] Various studies also explore links between area-level ethnic/cultural diversity and economic outcomes, typically using immigration as a diversity proxy. These typically find small, positive effects on productivity, innovation or employment, and in some cases, higher rents or

[2] A related and growing field looks at migrant diversity-performance links within firms and/or teams. The majority find small positive effects, but some find zero effects or distributional impacts that create winners and losers. Kerr (2013) and Nathan (2014) are two recent surveys.

other living costs (see inter alia Ottaviano and Peri (2005; 2006), Alesina et al (2013), Kemeny (2014) Nathan (2015) and Lewis and Peri (2011).)

So far, the only studies to combine firm-level and area-level analysis focus on migrant diversity. Trax et al (2012), using German plant-level panel data, find positive effects of both firm-level and area-level worker diversity on firm productivity. That is, migrant diversity creates externalities running from areas to firms – and the reverse. Kemeny and Cooke (2015) construct employer-employee data across 29 US states, finding both city-level effects of immigrant diversity on wages, and smaller firm-level effects. They suggest this represents positive, nontrivial spillovers from urban diversity to firms. By contrast, Lee (2014) uses cross-sectional data for UK small and medium-size firms (SMEs). He finds in-firm diversity-innovation links, but no evidence that area-level minority ethnic presence or diversity induce innovation at the firm level. However, London-based firms with more migrant owners and partners are more innovative than others, as are firms in high human capital cities.

3. Data and variables

My data is the UK Regional Development Agencies' National Business Survey (hence NBS), which ran annually from 2003 to 2009 across the English regions and Northern Ireland (the

Agencies were abolished in 2011).[3] The English data comprises 2,381 observations, weighted by employees and region to ensure national representativeness (Ipsos MORI, 2009). The NBS included questions about ethnicity and gender in 2008 and 2009. I use the 2008 cross-section, which provides most detail. The NBS has strengths and weaknesses. In particular, it asks a range of questions about 'owners, partners and directors', a broad definition of the TMT that reflects the literature. The 2008 data covers TMT size, ethnicity and gender mix, plus specific minority ethnic groups, distinguishes TMT members from the wider workforce, and includes four-digit industry codes (SICs) and detailed spatial identifiers. Conversely, there is no panel structure to the data, and it does not cover workforce human capital. To handle this, I use detailed small-area level workforce and demographic information from the Annual Population Survey (APS), where a boosted local sample allows for reliable sub-regional estimates.[4]

3.1 Key variables

Business turnover (income generated through trade of goods and services) is organised into seven bands in the NBS, ranging from 'up to £49,000 / year' to '£5m+ / year'.[5] Modelling diversity is less straightforward. A few authors (Lee, 2014; Ostergaard et al., 2011; Hunt and Gauthier-Loiselle, 2010) use a firm's share of minority ethnic individuals (or migrants). But this

[3] 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. The survey used a postal methodology with an online option, and used postal and email reminders. Fieldwork was conducted between October-December 2008.

[4] 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.

[5] The full coding for turnover is 1 (up to £49k), 2 (£50-99k), 3 (£100-499k), 4 (£500-999k), 5 (£1-1.99m), 6 (£2-4.99m) and 7 (£5m+).

allows for shares of 100% or close to it, which are not evidently ‘diverse’. Ottaviano and Peri (2006) show that population diversity is a product of both number and balance of identity groups in that population, and use a fractionalisation index to represent this. My data has information on the share of White/White British, Black/Black British, Asian/Asian British, ‘mixed’ and ‘other’ TMT members: these are large categories, but go beyond visible appearance. However, only 4.9% of firms have *any* minority TMT members (Table 1): a fractionalisation index of these groups is 87% zeroes, so has little variation across the sample. This also suggests that a polynomial will be hard to fit.

My preferred diversity measure is thus a dummy that takes the value 1 if the TMT has at i) least some minority ethnic members and ii) not 100% minority ethnic membership. To explore non-linearity, I fit the share of minority ethnic TMT members alongside the dummy. This allows me to separate a) the ‘effect’ of some diversity versus homogeneity and b) the slope of the TMT diversity coefficient for diverse firms, providing a rough sense of whether a nonlinear link is present. I use a fractionalisation index and alternative measures in robustness checks.

This approach also helps in identification. If ethnic diversity has some kind of link to firm performance, and my measured diversity is cruder than true diversity, then *ceteris paribus*, I am likely to have a lower bound on the true results.

3.2. Descriptives

Table 1 provides summary statistics. Average turnover is between £100-499k (corresponding to band '3'). The average top team has just 3.7% minority ethnic members; 2.9% of firms have all-minority TMTs. Minority TMT members are primarily of Asian origin. Firms are more diverse gender-wise, with an average of 26% female TMT representation: just under 10% of firms have all-female top teams. I find negative significant correlations between TMT minority ethnic shares and turnover, but positive and strongly significant TMT diversity-turnover links (Table A1, Online Appendix).

Table 1 about here

The average firm is 6-9 years old (banded '5') and has around 20 non-TMT staff (the biggest has over 12,000 employees). Just over 80% of firms are independently-owned or limited liability partnerships (LLPs); few are exporters; around a third have a formal business growth plan or provided staff training in the past year. Around a quarter report some product or process innovation; nearly 2/3 expect to invest in research and development (R&D) in the coming year. Only a minority have formalised 'innovation links' to universities or through specialist networks, but response rates are lower for these variables, which are reserved for robustness checks. Just over 47% of firms are in 'knowledge-intensive' sectors such as pharmaceuticals, software, or finance; just under 24% are in knowledge-intensive business services (KIBS) (Wood, 2006).[6]

[6] I use the definition of KIBS from Wood (2006). This includes financial intermediation, insurance and pension funding, auxiliary financial activities, real estate, legal, accountancy, hardware / software consultancy, data processing / database activities, advertising, market research, business / management consulting, architecture and engineering, technical testing, research and development.

The bottom panel of Table 1 gives NUTS2 (sub-regional) area-level characteristics. We can see substantial spatial variation in area demography, share of working age population with degrees and (to a lesser extent) employment density. Table 2 shows firms' location by more detailed NUTS3 (local authority) area type, using a Eurostat typology. These categories denote firms' immediate operating milieux.

Table 2 about here

More than 2/3 of firms are in some kind of urban locale (part of a large city); of these, around 15% are in London and surrounds, and 38% in London or 'second-tier' city-regions such as Manchester, Birmingham or Liverpool.

4. Identification

Identifying causal effects of team characteristics on firm-level outcomes throws up several challenges (Adams et al (2010) review these). First, some factors may simultaneously explain firm performance and TMT demographics: bigger, more diverse cities have larger home markets, plus more diverse firms. Second, some of these features – such as agglomeration economies – tend to persist over time. These issues lead to spurious correlations if not dealt with. Third, because of these wider factors successful firms may select into the largest markets, which *ceteris paribus* tend to have larger and more diverse populations. Not controlling for this leads up to (likely upward) bias in diversity coefficients (Card, 2010). Fourth, there may be selection within the TMT. If businesses observe a positive (negative) effect of top team composition on performance, they may adjust team composition to maximise (minimise) any positive (negative) consequences (Ozgen et al., 2013; Parrotta et al., 2014b). Fifth, all of these processes may operate differently across different firms, because of unobservable firm-level characteristics (Adams et al., 2010; Ozgen and De Graaff, 2013).

Selection issues cannot be eliminated in my data: I am unable to instrument for endogenous variables using historic data, or exploit an exogenous policy shifter, strategies used in other studies (Kerr and Lincoln, 2010; Parrotta et al., 2014a).[7] The analysis therefore provides associations, not causal effects: the goal is to render these linkages cleanly.

To do this I select a 'crisis' year, 2008, in which turnover-boosting external shocks are unlikely to occur or have occurred immediately preceding. I exploit the richness of the cross-sectional data to fit a large vector of observable firm characteristics. I estimate an Ordinary Least Squares (OLS) model that combines firm and area information (lagged job density, human capital stocks and minority ethnic population shares, plus the area's position in the UK urban hierarchy). This helps handle area-level omitted variables and simultaneity. Following Ozgen and De Graaff (2013), I also use Finite Mixture Modelling (FMM) to allow these firm-area-performance relationships to vary across different kinds of businesses. FMM provides a natural modelling of unobservable heterogeneity by probabilistically assigning firms into homogenous sub-samples, but keeps these pooled in the regression (Deb, 2008). This improves on OLS (which ignores

[7] I test lagged historic area demographic information and shift-share instruments. Neither passes first stage tests. Policy shocks such as East European countries' EU accession are unusable given the lack of panel structure.

unobservables) and on sub-sample analysis (FMM segmentation is a function of the regression, whereas sub-samples are defined *a priori* by the researcher so may miss relevant features).[8]

FMM is a latent class estimator that is essentially a form of unsupervised learning (Hastie et al., 2009). FMM has been used in a range of science and social science fields, as well as economics and geography (Heckman and Singer, 1984; Baum-Snow and Pavan, 2012; Brown et al., 2014). The probabilistic 'mixture' of homogenous classes is estimated semi-parametrically using maximum likelihood: the same statistical model applies, but each class has different parameters, allowing explanatory variables to have differing effects across components (Brown et al., 2014).

FMM requires that the total distribution of the data is a discrete mixture of distributions for homogenous groups. As well as picking the appropriate number of components, I therefore need to show that group assignment is both clean and better than random assignment.

5. Model and estimation

My basic model is a production function for firm *i* in sector *j* and area *a*:

$$Y_{ija} = f(\mathbf{DIV}\boldsymbol{a}_{\mathrm{ija}}\ , \mathbf{FCTRLS}\boldsymbol{b}_{\mathrm{ija}}\ , \mathbf{ACTRLS}\boldsymbol{c}_{ija}\ , J_j\ , A_a)\ u_{ija} \tag{1}$$

[8] Alternative potential identification strategies include a control function or a Heckman selection model. In tests, control function estimates are unstable and highly sensitive to choice of controls. Heckman estimation requires a plausibly exogenous selection variable, which is hard to identify in this instance.

Where Y is banded turnover and **DIV** is top management team ethnic diversity, fitted as i) the TMT diversity dummy, or ii) diversity dummy plus TMT minority ethnic share. *b* is the average marginal 'effect'. **FCTRLS** and **ACTRLS** are firm and area-level controls respectively; J and A are SIC1 industry and NUTS2 area dummies. Standard errors are clustered on SIC1.

To look at urban interactions, I fit:

$$Y_{ija} \quad = f(\mathbf{DIV}\boldsymbol{a}_{\mathrm{ija}}, b\mathrm{DIV}^{*}\mathrm{URB}_{\mathrm{ia}}, \mathrm{URB}_{\mathrm{a}}, \mathbf{FCTRLS}\boldsymbol{c}_{\mathrm{ija}}, \mathbf{ACTRLS}\boldsymbol{d}_{ia}, \mathrm{J}_{j}, \mathrm{A}_{a})\, \mathrm{u}_{ija} \qquad (2)$$

Where URB is a NUTS3 urban area dummy from the Eurostat typology. Specifically, I fit dummies for 'capital city-regions' (London and surrounds) and for 'urban city-regions' (London and large cities, e.g. Manchester, Birmingham or Liverpool). NUTS3 units are nested within NUTS2s, so can be fitted alongside area dummies. Here I am interested in *a* (the firm-level 'effect'), and *b*, the 'firm-city' combination of TMT and area characteristics.

Firm-level controls (**FCTRLS**) include number of owners/partners/directors, TMT gender diversity, firm age, number of non-TMT employees, firm legal status, innovation, workforce development activity, growth plans and operating capacity. Both TMT size and gender mix may affect top team performance (Apesteguia et al., 2012). Larger and more established businesses are likely to have higher turnover; age and size may also affect TMT demographics (Haltiwanger et al., 2013). Company type matters, since subsidiaries can access resources from parent firms (Javorcik, 2004); such corporate structures may also influence TMT choices. I fit dummies for UK subsidiaries, foreign subsidiaries, holding companies, and independents/LLPs, with ‘unknown’ the reference category. Innovation may feed through to higher turnover, so I fit separate dummies for whether the firm reports a product or a process innovation in that year. Crucially, firms’ human capital may explain apparent TMT ‘effects’ (Parrotta et al., 2014a). I fit dummies for whether firms have attempted to improve skills through training, and whether the firm has hard-to-fill vacancies. To approximate managerial capacity I fit dummies taking the value 1 if the firm has a codified growth plan and if it is operating at capacity.

In **ACTRLS** I fit the lagged area-level share of graduates as a further control for human capital available to the firm. This covers historic and persistent sub-regional conditions that may affect both firm performance and TMT demographics. Economically dense urban locations help firm productivity via agglomeration economies, raising turnover (Rosenthal and Strange, 2004); urban areas have more skilled and diverse populations, which may influence top team characteristics. I therefore fit the five-year lag of NUTS2 area employment density, area share of graduates, and area minority ethnic working age population.

5.1 Estimation

I estimate equations (1) and (2) in OLS, then in FMM, the latter estimated using maximum likelihood.[9] For OLS, collinearity is a potential concern: however, the mean variance inflation factor (1.27) is reassuring, as are raw results from the correlation matrix (Table A1). For FMM, I run the model as a mixture of normal distributions and run diagnostics to determine the optimal number of components. The FMM estimator solves iteratively for 2, … *C* components.

[9] A potential alternative estimator to OLS is an ordered logit. However, while turnover is banded the required proportional odds assumption may not hold.

Increasing *C* mechanically improves model fit statistics, but models with many components are less parsimonious and harder to interpret (Heckman and Singer, 1984).

I achieve convergence for up to four components (Table A2). However, components under 150 observations provide less reliable inference (Deb, 2008), particularly given the dummy variables and interactions. I therefore choose a three-component model that allows for robust interpretation.

Table 3 about here

Table 3 gives FMM performance information. The estimator assigns just over 78% of firms into component 1, about 16% into component 2 and just over 6% into component 3. Mean posterior probabilities show how clean this assignment is: specifically, the probability that firm *i* belongs to class *C* given Y_i, that firm's banded turnover. This statistic also indicates overall 'performance': scores should be close to one for the given probability*component cell. We can see that a three-component model performs well. Entropy measures component distinctiveness, varying from 0 (everybody has an equal probability of membership in all classes) to 1 (each individual has probability 1 in given class) (Ramaswamy et al., 1993). Entropy is just over 0.6, so FMM assignment is substantially better than random draws.

Figure 1 about here

Figure 1 shows the kernel density estimate of turnover for the pooled sample (bold line) versus each component (thin lines). Turnover is banded 1-8, which gives the distinctive 'peaks' on each line. The underlying distribution the pooled sample is a normal distribution; we can see that a three-component model 'compiles' back to this. Component 3 is least well modelled, so more caution is needed for these results. More detail is given in Section 7.

6. Pooled sample analysis

Table 4 gives OLS results for equation (1). Column 1 fits turnover and the TMT diversity dummy alone; the coefficient of $\hat{a}$ is 0.856, significant at 1%, which implies a firm with an ethnically diverse TMT is associated with an 8.56% rise in turnover compared to a firm with a homogenous top team. Column 2 adds controls, substantially improving model fit: $\hat{a}$ drops by almost half, to 0.449, again significant at 1%. For a hypothetical average-turnover firm this cashes out to a 4.49% turnover jump, or £11,225. The TMT gender diversity dummy is also positive at 0.134, significant at 1%, and remains positive in all other specifications here.

Column 3 tests for a nonlinear DIV-turnover relationship by fitting the diversity dummy (some diversity versus none) plus the share of minority ethnic TMT members (the slope). In this case the dummy coefficient rises to 0.557 and the slope coefficient is -0.300, both significant at 1%. This suggests an N-shaped relationship overall, with some diversity a positive, but a higher share of minority ethnic TMT presence associated with lower turnover. Column 4 confirms this by fitting two dummies, for diversity and for all-minority ethnic TMTs. The diversity coefficient is 0.435 and the all-minority coefficient is -0.322; again all coefficients are significant at 1%.

Table 4 about here

6.1 Sensitivity checks

Table 5 puts these results through checks for alternative diversity metrics, omitted variables and functional form. Overall, coefficients of DIV remain largely unchanged, suggesting the basic specification is appropriate.

Table 5 about here

Column 1 fits the main result from Table 4. Column 2 refits DIV as a fractionalisation index of ethnic groups. As discussed in section 3, the data structure means the Index is mostly zeroes, and the coefficient here is – not surprisingly – insignificant.[10]

Column 3 removes sole traders: coefficients of DIV shift downwards slightly. Columns 4 and 6 run more precise industry controls, with dummies for knowledge intensive and knowledge intensive business services firms respectively. TMT diversity may be especially important in knowledge-intensive settings (Berliant and Fujita, 2012), so columns 5 and 7 interact these with

[10] I also run checks with the five-year lag of recent migrants (those in the country 3 years or less). This does not affect firm diversity coefficients. Results available on request.

DIV. Industry dummies are both negative on revenue, most likely because revenue in these sectors is pro-cyclical and the UK was heading towards recession in 2008. Total effects are lower than DIV alone, implying smaller TMT diversity 'effects' in knowledge-intensive and KIBS firms: however, partial effects are insignificant or only marginally significant. Column 8 tests a different angle, interacting DIV with the product innovation dummy: this suggests very little difference in linkages between firms with and without product innovations, and again the interaction term is non-significant.[11] Column 9 adds additional innovation-related controls: these have low response rates, so the sample drops to 1,284 observations. TMT diversity grows to 0.654, significant at 1%: minority ethnic TMT share stays negative but is no longer significant.

TMT diversity may enable international market access, or reflect a desire to raise exports (Docquier and Rapoport, 2012). Column 10 adds firms' share of foreign sales and interacts this with DIV. As other studies have found, TMT diversity has a bigger link with firm revenue the more export-intensive the company in question: but the partial effect is not significant. Finally I test for functional form. Column 11 fits two-way (industry*area) clustered standard errors. In both cases standard errors increase but coefficients of DIV remain the same.[12]

6.2 Firm-city analysis

Table 6 shows results for the firm-city interactions model (2). Interactions indicate current connections (or lack of) between TMT ethnic mix and firms' immediate local environment.

[11] A test with process innovation generates a similar result. Results available on request.

[12] Clustering standard errors on NUTS2 area does not change the main result either. Result available on request.

Table 6 about here

The results show suggestive positive interactions. Urban area dummies are always positive significant, as expected (columns 1 and 3). For these models, TMT diversity coefficients increase slightly, from 0.449 to 0.453 (capital city-region) and 0.454 (urban areas) and are significant at 1%. The interaction models (columns 2 and 4) show that the *total* link from DIV to revenue gets bigger for urban firms, although the interaction terms are not significant. For TMT-diverse firms in the capital city-region this is 0.828 (0.543 + 0.285), compared to a non-significant 0.295 for non-London diverse firms. For diverse firms in large urban areas, the total 'effect' is 0.569 (0.334 + 0.215), compared to 0.340 for diverse firms elsewhere (significant at only 10%).

7. Finite mixture analysis

How does our sample of firms break down? Table 7 gives summary statistics for the three components from the finite mixture modelling (FMM). I also provide a class-weighted average: the closeness of modelled and observed sample means is reassuring. The top panel of Table 7 covers firms' turnover, TMT characteristics and detailed firm information; the second panel gives firms' industry characteristics; the third and fourth panels show area-level characteristics.

Table 7 about here

Component 1 comprises the majority of firms (1858 observations): they have smaller-than-average workforces, about average turnover, and are located principally in NUTS3s outside London and larger cities. These firms' minority ethnic TMT share, 3.7%, matches the pooled average. They are less likely to have a diverse TMT (1.6% versus 2%). They are about the same age as the average firm and are more likely to be independently owned or a partnership. They are less likely to have a formal growth plan, to have provided training, or to have innovated, and a little less likely to be planning R&D activity, use university-industry links or specialist networks. They are spread across sectors: more detailed SIC2 analysis, available on request, shows higher-than average shares in accommodation, warehousing and heavier manufacturing, but also architecture and engineering, information services and scientific R&D. They are less likely to be 'knowledge-intensive' than the average firm, but more likely to be in knowledge-intensive business services. Location shares are above average for smaller city-regions (28.7% vs 28.2%) and non-urban areas (34.9% vs 33.9%).

Component 2 comprises about 16% of observations. These are high-turnover companies (£1-1.99m) with large workforces (105 versus 23 in the pooled sample). They are more likely than average to be knowledge-intensive, with a mix of high-value manufacturing, energy and public sector activities such as education, museums and the arts. They are most commonly located in Greater London (especially outer London), the Home Counties, and the Birmingham, Leeds and Sheffield city-regions (Table A3). They have a higher than average share of diverse TMTs (3.5% versus 2%), a slightly higher minority ethnic TMT share and a higher than average share of Asian TMT members. They are slightly older than average, and more likely to be UK/foreign subsidiaries or holding companies. Almost half have a formal growth plan (versus 34.2% of the pooled sample), and they are more likely to have provided training, innovated (especially process innovation), do R&D, use university-industry connections and exploit specialised networks.

Component 3 is the smallest, at 152 observations (6.4% of the sample). These are younger and lower-turnover firms (£50-99k), with the smallest workforces (four staff on average), spread across a range of sectors but located in the most diverse and job-dense areas, especially in Inner London but also Greater Manchester, Merseyside and Newcastle-Gateshead (Table A3). They have lower than average minority ethnic TMT shares, and the lowest shares of all-minority TMTs (but the highest shares of female TMT members). They are most likely to have introduced a product innovation, but least likely to do R&D, or pursue formal channels for innovation purposes. They are also least likely to have a formal business plan or to have provided formal training. With a broad sectoral spread, they are least likely to be knowledge-intensive or KIBS businesses.

7.1 FMM results

Table 8 refits (1) using these components, and confirms that the pooled sample hides substantial variation between groups of firms. Column 1 fits the TMT diversity dummy. Component 1 firms, the majority of businesses, show no link between TMT diversity and turnover in any specification, with coefficients insignificant and close to zero. Component 2 firms, which are larger, more knowledge-intensive, have higher turnover and the most diverse top teams, show a positive link from TMT diversity to turnover. Component 3 firms, the smallest, youngest, least knowledge-intensive and most urbanised, indicate a large negative link from TMT diversity to turnover (0.833, significant at 1%) compared with either all-minority or all-majority TMTs.

Table 8 about here

I next estimate (2) for the FMM segments, testing for 'firm-city' connections between TMT demographics and area characteristics. Column 2 interacts TMT diversity with dummies for capital city-region locale, Column 3 any large urban area locale (capital city plus large metros).

As set out earlier, TMT diversity-performance links may be amplified in urban locations because of agglomeration economies, area demography, or both. Conversely, many urban firms (especially those in non-tradable sectors) face higher competition and costs, which negatively impact on revenue. Diverse firms in segregated and/or poorer neighbourhoods may also have lower revenue. Positive firm-area links may be larger for firms in knowledge-intensive sectors (because TMT diversity aids innovation), and for smaller/younger firms (if urban milieux act as 'nurseries').

As in Table 8, the majority of firms (component 1) show no significant diversity-performance links, and no partial effects are significant in the interactions. Results for component 2 firms differ across area type. For component 2 firms in London and surrounds (column 2), there is a large amplifying effect on TMT diversity (1.405, significant at 1%). This London link drives the association in the main results, as the diversity-performance link for these firms in other areas is now close to zero and non-significant. Conversely, looking at urban locales as a whole (column

3), we find a strong independent link from urban location to performance (significant at 1%), but the partial effect is zero, and the coefficient of TMT diversity is positive non-significant.

Component 3 firms also show differing results across locales. When these firms are in London and surrounds, the partial effect is negative significant (column 2), and the total diversity-performance 'effect' is higher outside the capital than inside (0.480 vs 0.144, both significant at 1%). However, looking at urban areas as a whole (column 3), there are very large, significant interactions between TMT diversity and urban locale (2.021, significant at 1%, with a total 'effect' of 1.705), while for diverse firms elsewhere, diversity is negatively linked to performance (-0.316, significant at 5%) as in the firm-level analysis in Table 8. Unlike component 2 firms, then, here the firm-city link is for second tier metros, not London.

Firm-city interactions may reflect economic factors, demographic factors or both. To try and parse this further, I fit a three-way interaction between TMT, locale and lagged area minority ethnic population share. This is a crude test, so results should be interpreted with some care.[13] For component 2 firms I find a strong positive partial effect (3.481, significant at 1%), while all main effects are positive non-significant. For component 3 firms, the partial effect is negative significant, while all main effects are positive significant. This suggests that for component 2 firms, TMT diversity gains are closely linked to area demography, while for component 3 firms, TMT diversity is closely linked to urban agglomeration.

[13] Results available on request. Regressions with TMT diversity *capital city region * capital city-region demographics do not converge.

8. Discussion

This paper looks at links between 'top team' ethnic diversity and business performance for a cross-section of English firms, exploring both firm-level connections and 'firm-city' level interactions. It uses Finite Mixture Modelling to test how these links differ across firm types. It is one of very few studies to look at the economics of diversity at firm and city-level, and the only study I am aware of to focus directly on ethnic diversity, rather than use migration as a proxy.

There are three main results. First, in the pooled sample I find positive connections between firm turnover and top team ethnic diversity, and suggestive evidence of non-linearity. This may reflect production complementarities (e.g. through innovation and/or task specialisation), improved market access or both. Second, I find no diversity-performance link for the majority of businesses: OLS results seem driven by a minority of larger, high-turnover, knowledge-intensive firms concentrated in Greater London and some large conurbations.

Third, controlling for area-level characteristics, I find positive interactions between firms' top team diversity and urban locales, in line with migrant-based studies by Trax et al (2015) for Germany and Kemeny and Cooke (2015) for the US, but contra Lee (2014) for the UK. These links are only statistically significant for two groups of businesses, which together account for about 20% of the sample, and vary across urban locations. For the bigger group – large, high-turnover, knowledge-intensive firms – locating in London and surrounds appears to amplify top team diversity-performance links, while firms in this group based elsewhere show no such relationship. I find suggestive evidence that London's demography is an important factor behind these 'firm-city' interactions.

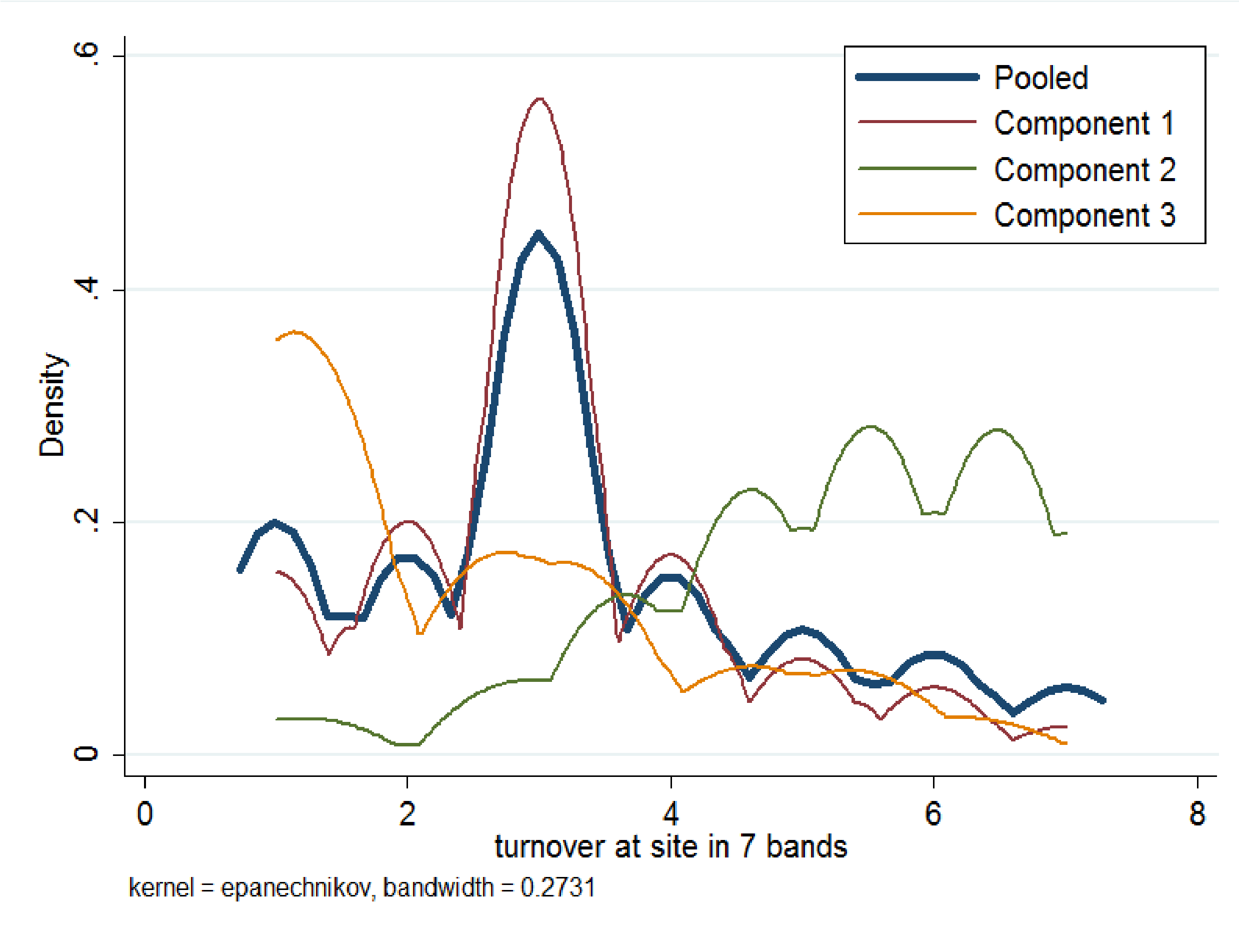
For the smaller group – younger, smaller firms and microbusinesses in less knowledge-intensive sectors – urban location *as a whole* amplifies diversity-performance links, but London location is associated with lower turnover than location elsewhere. I suggest two main reasons for this. First, these firms may be located in poorer, more segregated areas (especially inner London) and other metros, which may offer thinner local opportunities. A second, more basic explanation is that urban areas offer both affordances (agglomeration economies, large home markets) and constraints (competition, costs), and that for some small firms, second tier cities offer a better balance than London: such firms are typically not knowledge-intensive, so may not experience net 'nursery city' benefits in the largest urban locations. Separate OLS regressions, available on request, show that knowledge-intensive small companies and microbusinesses in London and surrounds *do* have higher turnover than those outside, providing some support for this idea.

There are a number of caveats. Crucially, my data is cross-sectional, so results have to read as associations. Firm-city interactions likely reflect selection into urban areas as well as city-to-firm channels, as other studies using instruments or GMM have found. Second, the data structure also reduces the precision of my estimates, with some controls handled using workarounds. Third, I have detailed TMT information but do not directly observe workforce characteristics: workforce human capital, demographics or both may play a separate role in explaining firm performance. I handle this using small-area data; previous analysis for London firms suggests that both TMT and wider workforce characteristics matter to firm innovation (Nathan and Lee, 2013), suggesting that true TMT-level processes are observed in my data.

This leaves several topics for future research. Worker-firm panel data, which is rare in the UK, would substantially improve analysis – for example, through testing for decay effects of diversity over time. More challenging is to find exogenous shifters of workforce or TMT composition. These occur rarely (see Ahern and Dittmer (2012)), so researchers tend to rely on lab studies or instruments. The external validity of the former is moot, especially given the urban context examined here. However, lab studies do highlight the importance of task and organisational context, which seem to condition the impacts of group and firm demographics (Mannix and Neale, 2005). Similarly, individual attributes and preferences can impact team performance in ways that are hard to untangle in real world scenarios (Azmat and Petrongolo, Forthcoming). *In situ* research has been largely qualitative to date. Structured, large-scale analysis would be a major step forward.

Figures and tables

Figure 1: Kernel density of banded turnover.



Source: NBS.

Table 1. Summary statistics.

VARIABLES	N	mean	sd	min	max
turnover at site (banded)	2,381	3.361	1.608	1	7
ethnic-diverse TMT	2,381	0.020	0.139	0	1
all minority-ethnic TMT	2,381	0.029	0.167	0	1
% minority ethnic owners/partners/directors	2,381	0.037	0.176	0	1
% black owners/partners/directors	2,381	0.004	0.056	0	1
% asian owners/partners/directors	2,381	0.025	0.148	0	1
% mixed ethnicity owners/partners/directors	2,381	0.003	0.054	0	1
% other ethnicity owners/partners/directors	2,381	0.004	0.056	0	1
ethnic fractionalisation index of TMT	2,381	0.110	0.302	0	1
gender-diverse TMT	2,381	0.341	0.474	0	1
all-female TMT	2,381	0.099	0.299	0	1
% female owners/partners/directors	2,381	0.257	0.332	0	1
No. of salaried employees (excluding owners)	2,381	22.85	273.1	0	12,435
number of owners/partners/directors	2,381	2.158	4.028	1	100
years business in operation (banded)	2,381	5.245	1.225	1	6
firm is subsidiary of UK parent	2,381	0.034	0.181	0	1
firm is subsidiary of foreign parent	2,381	0.016	0.124	0	1
firm is ultimate holding company	2,381	0.016	0.125	0	1
firm is LLP or independent	2,381	0.871	0.335	0	1
share of foreign sales (banded)	2,381	0.659	1.395	0	6
new product innovation in last 12 months	2,381	0.181	0.385	0	1
new process innovation in last 12 months	2,381	0.078	0.268	0	1
growth plan dummy	2,381	0.342	0.475	0	1
business is operating below capacity	2,381	0.678	0.467	0	1
hard-to-fill vacancies in past 12 months	2,381	0.678	0.467	0	1
business provided some training in past 12 months	2,381	0.354	0.478	0	1
firm expects to do R&D investment in next 12 months	2,317	0.634	0.482	0	1
business uses U-I links for R&D	1,407	0.191	0.393	0	1
business uses specialist networks for info	1,761	0.422	0.494	0	1
firm is knowledge intensive	2,381	0.473	0.499	0	1
firm is knowledge intensive business services	2,381	0.238	0.426	0	1
NUTS2 % recent migrants, 2004	2,381	0.018	0.018	0.002	0.108
NUTS2 % minority ethnic population, 2004	2,381	0.070	0.088	0.007	0.405
NUTS2 % working age population with NVQ4 or above, 2004	2,381	0.090	0.056	0.025	0.313
NUTS2 job density, 2004	2,381	0.001	0.002	0.000	0.016

Source: NBS.

Table 2. Firm NUTS3 location typology.

EU metro typology	Freq.	Percent	Cumulative
Capital city region NUTS3	363	15.25	15.25
Second tier city region NUTS3	538	22.6	37.84
Smaller metro region NUTS3	673	28.27	66.11
Other NUTS3 regions	807	33.89	100
Total	*2,381*	*100*	

Source: NBS.

Table 3. FMM model performance.

Component	**1**	**2**	**3**
Frequency	1858	371	152
Percent	78.03	15.58	6.38
Mean posterior probability	**Most likely latent class / component**		
	LC1	**LC2**	**LC3**
p1	**0.813**	0.186	0.000
p2	0.164	**0.835**	0.000
p3	0.101	0.025	**0.874**
Entropy		0.618	
AIC		6934.556	
BIC		7933.679	
Sample size adjusted BIC		7384.021	
# free parameters		173	
Log likelihood		-3294.278	

Source: NBS.

Table 4. Firm analysis: OLS results.

	(1)	(2)	(3)	(4)
ethnic-diverse TMT	0.856***	0.449***	0.557***	0.435**
	(0.213)	(0.129)	(0.132)	(0.130)
% ethnic owners/partners/directors			-0.300***	
			(0.080)	
all minority-ethnic TMT				-0.322***
				(0.088)
number of owners/partners/directors		0.011	0.011	0.011
		(0.015)	(0.015)	(0.015)
gender-diverse TMT		0.134***	0.130***	0.130***
		(0.032)	(0.033)	(0.033)
No. of employees who receive a salary		0.000**	0.000**	0.000**
		(0.000)	(0.000)	(0.000)
years business in operation		0.289***	0.285***	0.285***
		(0.012)	(0.012)	(0.012)
firm is subsidiary of UK parent		1.201***	1.198***	1.198***
		(0.236)	(0.231)	(0.230)
firm is subsidiary of foreign parent		1.866***	1.855***	1.854***
		(0.172)	(0.172)	(0.173)
firm is ultimate holding company		0.866***	0.860***	0.858***
		(0.227)	(0.225)	(0.226)
firm is LLP or independent		0.340**	0.338**	0.338**
		(0.117)	(0.121)	(0.121)
hard-to-fill vacancies in past 12 months		0.471***	0.478***	0.478***
		(0.101)	(0.100)	(0.101)
business provided some training in past 12 months		0.866***	0.864***	0.864***
		(0.093)	(0.093)	(0.093)
new product innovation in last 12 months		0.166*	0.162*	0.162*
		(0.074)	(0.074)	(0.074)
new process innovation in last 12 months		-0.002	-0.000	-0.001
		(0.163)	(0.160)	(0.160)
growth plan dummy		0.607***	0.606***	0.607***
		(0.087)	(0.087)	(0.087)
business is operating below capacity		-0.116*	-0.114*	-0.113*
		(0.062)	(0.061)	(0.061)
job density 2004		-0.352	0.242	0.236
		(10.242)	(10.218)	(10.192)
% minority ethnic population 2004		0.672**	0.734**	0.741**
		(0.289)	(0.297)	(0.302)
% working age population with NVQ4 or above 2004		0.747	0.786	0.787
		(0.814)	(0.795)	(0.794)
Observations	2381	2381	2381	2381
R^2	0.071	0.358	0.359	0.360

Source: NBS. Constant not shown. Standard errors in parentheses. All models use sic1 and nuts2 dummies. HAC standard errors clustered on sic1. * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Firm analysis: sensitivity checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ethnic-diverse TMT	0.449***		0.402**	0.457***	0.893**	0.436**	0.491**	0.452***	0.560**	0.337**	0.449***
	(0.129)		(0.135)	(0.127)	(0.324)	(0.130)	(0.165)	(0.122)	(0.186)	(0.141)	(0.135)
ethnic fractionalisation index of TMT		-0.139									
		(0.090)									
firm is knowledge intensive				-0.211**	-0.200**						
				(0.077)	(0.078)						
ethnic-diverse TMT * knowledge-intensive firm					-0.689*						
					(0.364)						
firm is knowledge intensive business services						-0.303***	-0.298***				
						(0.033)	(0.034)				
ethnic-diverse TMT * KIBS firm							-0.259				
							(0.175)				
ethnic-diverse TMT * product innovation								-0.016			
								(0.428)			
new product innovation in last 12 months	0.166*	0.173*	0.167**	0.167*	0.169*	0.169**	0.168**	0.166*	0.128	0.165*	0.166*
	(0.074)	(0.078)	(0.066)	(0.074)	(0.076)	(0.071)	(0.071)	(0.076)	(0.070)	(0.075)	(0.099)
firm expects to do R&D investment in next 12 months									0.252		
									(0.148)		
business uses U-I links for R&D									0.078		
									(0.090)		
business uses specialist networks for info									-0.020		
									(0.076)		
ethnic-diverse TMT * share of foreign sales										0.132	
										(0.187)	
share of foreign sales banded										-0.001	
										(0.030)	
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2381	2381	2102	2381	2381	2381	2381	2381	1284	2381	2381
R^2	0.358	0.358	0.344	0.359	0.360	0.362	0.362	0.358	0.405	0.359	0.358

Source: NBS. Controls as in Table 4. Constant not shown. Standard errors in parentheses. All models use sic1 and nuts2 dummies. HAC standard errors clustered on sic1. * p<0.1, ** p<0.05, *** p<0.01.

Table 6. Firm and city analysis: OLS results.

	(1)	(2)	(3)	(4)
ethnic-diverse TMT	0.453***	0.295	0.454***	0.340*
	(0.126)	(0.192)	(0.125)	(0.159)
TMT eth diversity * capital city region		0.543		
		(0.375)		
NUTS3 capital city region	0.300**	0.285**		
	(0.121)	(0.110)		
TMT eth diversity * urban city region				0.215
				(0.216)
NUTS3 urban city region			0.339**	0.334**
			(0.109)	(0.108)
Controls	Y	Y	Y	Y
Observations	2381	2381	2381	2381
R^2	0.359	0.360	0.360	0.360

Source: NBS. Controls as in Table 4. Constant not shown. Standard errors in parentheses. All models use sic1 and nuts2 dummies. HAC standard errors clustered on sic1. * p<0.1, ** p<0.05, *** p<0.01.

Table 7. FMM segments.

Characteristic	Percentage of firms				
	Pooled	**Comp 1**	**Comp 2**	**Comp 3**	***C1-3 weighted***
turnover at site in 7 bands	3.361	3.075	5.226	2.296	*3.360*
% minority ethnic TMT	0.037	0.037	0.038	0.029	*0.036*
% black owners/partners/directors	0.004	0.004	0.004	0.000	*0.004*
% asian owners/partners/directors	0.025	0.025	0.029	0.015	*0.025*
% mixed ethnicity owners/partners/directors	0.003	0.003	0.003	0.007	*0.003*
% other ethnicity owners/partners/directors	0.004	0.004	0.002	0.008	*0.004*
all minority-ethnic TMT	0.029	0.030	0.024	0.020	*0.029*
ethnic-diverse TMT	0.020	0.016	0.035	0.026	*0.020*
% female owners/partners/directors	0.257	0.267	0.199	0.276	*0.257*
gender-diverse TMT	0.341	0.343	0.342	0.316	*0.341*
No. of employees who receive a salary (excl. owners)	22.85	7.792	105.900	4.066	*22.841*
number of owners/partners/directors	2.158	2.104	2.571	1.809	*2.158*
years business in operation (banded)	5.245	5.211	5.456	5.151	*5.245*
firm is subsidiary of uk parent	0.034	0.028	0.065	0.033	*0.034*
firm is subsidiary of foreign parent	0.016	0.011	0.040	0.007	*0.016*
firm is ultimate holding company	0.016	0.014	0.024	0.020	*0.016*
firm is llp or independent	0.871	0.882	0.830	0.849	*0.872*
new product innovation in last 12 months	0.181	0.178	0.183	0.204	*0.180*
new process innovation in last 12 months	0.078	0.071	0.113	0.072	*0.078*
growth plan dummy	0.342	0.322	0.491	0.230	*0.342*
business is operating below capacity	0.678	0.680	0.682	0.638	*0.678*
hard-to-fill vacancies in past 12 months	0.678	0.174	0.280	0.125	*0.187*
business provided some training in past 12 months	0.354	0.328	0.526	0.243	*0.353*
firm expects to do R&D investment in next 12 months	0.634	0.626	0.694	0.583	*0.634*
business uses U-I links for R&D	0.191	0.182	0.260	0.098	*0.189*
business uses specialist networks for info	0.422	0.419	0.454	0.385	*0.352*
primary (a-c)	2.35	2.53	1.62	3.29	*2.44*
manufacturing and energy (d-e)	12.68	12.57	15.36	15.79	*13.21*
construction (f)	8.02	8.12	6.47	9.87	*7.97*
wholesale and retail trade; repair (g)	21.04	20.54	23.72	25.66	*21.36*
hotels and restaurants (h)	6.47	7.05	2.16	6.58	*6.26*
transport/storage/comms (i)	3.70	3.83	4.58	2.63	*3.87*
financial intermediation; real estate; bus. services (j-k)	36.92	38.08	34.23	30.92	*37.02*
public sector; health; other community services (l-o)	8.82	7.28	11.86	5.26	*7.86*
knowledge intensive industry	0.473	0.473	0.501	0.408	*0.473*
knowledge intensive business services	0.238	0.248	0.199	0.211	*0.238*
% NUTS2 minority ethnic pop 2004	0.070	0.068	0.076	0.076	*0.070*
% NUTS2 working age population with degrees 2004	0.090	0.089	0.094	0.092	*0.090*
NUTS2 job density 2004	0.001	0.001	0.001	0.002	*0.001*
NUTS3 Capital city region	15.25	14.96	15.36	18.42	*15.24*
NUTS3 Second tier metro city region	22.6	21.42	28.84	21.71	*22.59*
NUTS3 Smaller metro city region	28.27	28.74	26.42	26.97	*28.27*
NUTS3 other area type	33.89	34.88	29.38	32.89	*33.90*
Observations	*2381*	*1858*	*371*	*152*	

Table 8. Firm and city analysis: FMM results.

	Comp 1	Comp 2	Comp 3	Comp 1	Comp 2	Comp 3	Comp 1	Comp 2	Comp 3
ethnic-diverse TMT	0.024	0.488*	-0.833***	0.028	-0.043	0.480***	-0.059	0.246	-0.316**
	(0.208)	(0.289)	(0.012)	(0.240)	(0.141)	(0.073)	(0.382)	(0.387)	(0.159)
TMT eth diversity * capital city region				-0.750	1.405***	-0.336***			
				(0.510)	(0.338)	(0.060)			
NUTS3 capital city region				0.239**	0.042	0.286*			
				(0.106)	(0.242)	(0.163)			
TMT eth diversity * urban city region							-0.060	-0.008	2.021***
							(0.344)	(0.369)	(0.198)
NUTS3 urban city region							0.271***	0.352***	-0.023
							(0.044)	(0.125)	(0.058)
Controls		Y			Y			Y	
Observations		2381			2381			2381	
Log-Likelihood		-3294.278			-3339.369			-3358.967	

Source: NBS. Controls as in Table 4. Standard errors in parentheses. All models use sic1 and nuts2 dummies. HAC standard errors clustered on sic1. * p<0.1, ** p<0.05, *** p<0.01.

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