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Top Team Diversity and Business Performance: Latent Class Analysis for Firms and Cities

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ABSTRACT

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A growing number of studies find linkages between workforce diversity and business performance, but key aspects of this relationship remain unclear. First, within the firm, the role of 'top team' demography on firm outcomes is surprisingly little understood. Second, urban location may amplify firm-level processes, but almost no studies test these firm-area interactions. I deploy English cross-sectional data to explore these issues, using latent class analysis to tackle firm-level heterogeneity. I find evidence of positive links in some firm classes, both linear and non-linear, and suggestive evidence that ethnic top team diversity is amplified in the London city-region.

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1. Introduction

This paper asks: what are the links between the demographic composition of 'top teams' in firms, and the performance of those firms? In particular, what roles might ethnic or gender diversity play in shaping firm revenues?

These questions are highly relevant to public and policy debate. Gender equality is a long-standing policy agenda. And as many Western countries become more ethnically diverse, commentators debate whether more cosmopolitan societies are economically or socially desirable (Florida, 2002; Gilroy, 2004), or whether such diversity has costs (Collier, 2013; Goodhart, 2013). Understanding *where* changes may take place is of critical importance. To date, most empirical analysis has focused at area level (for reviews see Nathan (2012), Kemeny (2014) and Lewis and Peri (Forthcoming)). However, many economic impacts occur within firms (Kerr, 2013). In theory, diversity in firms has ambiguous effects on company performance. More diverse workforces may be more creative and innovative, improve market access or allow for greater task specialisation; conversely, trust may be lower, making organisations less efficient. A small but growing number of firm-level studies have tested links between workforce diversity and business outcomes, most finding some positive effects (Nathan, 2012; Azmat and Petrongolo, Forthcoming).

Key aspects of these diversity-performance links remain unclear. First, are linkages linear or non-linear? If so, there may be 'optimal' levels of diversity (Ashraf and Galor, 2013). Second, do links operate differently within the firm? The demographics of a firm's owners, partners and

directors – the 'top management team' – seem highly salient (Hambrick and Mason, 1984).

Third, are there interactions between firm demography and area characteristics? In particular, ethnic diversity 'effects' in firms may be amplified in cities through agglomeration economies, urban diversity or both.

I use a cross-sectional dataset of over 2,000 English firms to explore these issues. My data allows me to specify 'top management team' (TMT) ethnic and gender diversity, as well as a range of firm characteristics and outcomes. Building on work by Ozgen and De Graaff (2013), I get closer to causality by using finite mixture modelling to tackle unobserved firm-level heterogeneity (Heckman and Singer, 1984): this approach also allows for rich descriptive analysis of firm classes within the sample. Overall, I find some evidence of positive diversity-performance associations. However, ethnic and gender TMT diversity have varying relationships to firm turnover within firm classes, and relative to each other. The largest and most established companies show a linear link from ethnic diversity to revenue; other groups, predominantly businesses that are smaller and less formalised in working structures, seem to have non-linear relationships (U-shape for ethnic diversity, N-shape for gender). Strikingly, I find some signs of capital city amplification 'effects' for the smallest, youngest and most financial services-orientated firms. By contrast, second tier metro locations exhibit decreasing effects.

The paper is one of very few to combine within-firm and urban scale analysis in this way. Nathan and Lee (2013) look at top teams for London firms. Trax et al (2012) and Lee (2014) explore firm-city interactions, but for the whole workforce (and in Lee, only for a cross-section of SMEs). Ozgen and De Graaff (2013) use a latent class approach for Dutch data, but are unable

to distinguish senior staff. The paper thus contributes to the growing 'economics of diversity' literature (Nathan, 2012), to the established literature on gender and business performance (Azmat and Petrongolo, Forthcoming), to work on high-skill migration (Kerr, 2013) and on management teams (Certo et al., 2006).

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 descriptive analysis, while Section 7 presents the main results and robustness checks. Section 8 extends the analysis to urban areas. Section 9 concludes.

2. Framework

Intuitively, 'diversity' refers to the mix of groups in a society, or as in this case, the mix of individuals in a group. Following Ottaviano et al (2007), I define 'diversity' in terms of number (of identity groups) and evenness (of groups' distribution).

In theory, the link from top management team demographics to business performance metrics such as turnover is ambiguous. One view is that diverse teams may benefit from a wider range of ideas, perspectives and experiences than homogenous teams, which may raise organisational creativity (Page, 2007). These effects may be particularly important in knowledge-intensive industries, or in problem-solving situations in any firm (Mannix and Neale, 2005). Ethnic diversity may also raise performance via network externalities – for instance, diasporic links to

'home' countries that improve market access (Foley and Kerr, 2013). Co-ethnic networks may also lower transactions costs and aid knowledge diffusion, which has become increasingly important under globalisation (Docquier and Rapoport, 2012). Ethnic diversity - for example from immigration - may also facilitate greater task specialisation (Peri, 2012). Conversely, trust and bonding social capital may be lower in diverse teams than for homogenous groups, so that decision-making is harder and organisations become less productive (Alesina and Ferrara, 2005). Some diasporic links may be more valuable than others. Female or minority-dominated top teams may also experience greater discrimination from suppliers and investors than homogenous firms.

Firm-level empirical research to date has tended to focus on *overall* workforce diversity. Ethnicity analysis is still relatively rare. Studies by Ozgen et al (2013) and Parrotta et al (2014a; 2014b) find positive links from ethnic diversity to firm innovation and productivity. Conversely, Maré et al (2013) and Maré and Fabling (2011) find no such links. Kerr et al (2013) link skilled migration to higher employment in US firms; Foley and Kerr (2013) suggest that skilled migrants help US multinationals access migrants' 'home' countries. Gender analysis is more common (for a review, see Azmat and Petrongolo (Forthcoming)) and typically suggests that gender diversity has positive effects on business performance. In a recent study of Dutch retail, for instance, Delfgaauw et al (2013) find that gender-balanced stores perform best in a sales tournament. Lab studies by Apesteguia et al (2012) and Hoogendoorn and van Praag (2013) also suggest that gender-diverse teams perform better than homogenous teams in sales games.

Three areas of the field are less well explored. First, the shape of a given diversity-performance relationship may not be linear (Ashraf and Galor, 2013). As Ashraf and Galor point out, this

may also vary across country or sector contexts. In Danish firms, for instance, Ostergaard et al (2011) find no evidence for ethnicity or gender non-linearity; by contrast Lee (2014) finds N-shaped links from ethnic diversity to innovation in UK SMEs.

Second, diversity-performance channels may operate differently *within* the firm. Senior management demographics may have particularly important impacts, given that 'top teams' take strategic decisions and set the overall direction of the business (Hambrick and Mason, 1984). TMT empirical literature highlights the importance of top team demographics (Certo et al., 2006; Adams et al., 2010), but surprisingly few studies look at ethnicity and gender dimensions of TMTs. One exception is Ahern and Dittmer (2012) who suggest that the introduction of gender quotas for Norwegian company boards led to less-experienced top teams in the short term, lowering profits.

Third, there may be important interactions between firm demography and area characteristics. In particular, the productivity-enhancing effects of cities or urban locations may amplify ethnic diversity-performance channels in firms. Urban demographics may also play a role, if diverse urban milieux present larger local markets to sell into. Conversely, urban segregation may limit the potential for diverse firms to generate sales outside specific communities. A number of area-level studies find positive connections from diversity to aggregate economic outcomes (see Nathan (2012) for a review of this literature). However, very few studies explicitly examine firm-urban linkages. Trax et al (2012) find strong evidence of spillover effects from area-level cultural diversity to German firm performance, and from workforce diversity to regional outcomes. In the UK, Nathan and Lee (2013) find that firms in London benefit from diverse

home markets. However, Lee (2014) finds little evidence of links between urban demographics and SME innovation.

3. Data and variables

Data is drawn from the UK Regional Development Agencies' National Business Survey (hence NBS), which was conducted every year from 2003 through to 2009 across the nine English regions and Northern Ireland (the Agencies were formally abolished in 2011).[1] The NBS included questions about owner/partner ethnicity and gender in 2008 and 2009. I use the 2008 cross-section, which provides the most detailed turnover information. The raw data for England comprises 2,381 observations, weighted by employee numbers and region (Ipsos MORI, 2009).

The NBS has strengths and weaknesses. The UK has surprisingly few rich sources of firm-level data, and the NBS is a single source that asks detailed 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 fixed effects alongside firm-level controls. As such it is substantially more informative than other business-level datasets such as the ARD, and fuller in its coverage than other UK surveys. Conversely, some questions vary from year to year, and there is no panel structure to the data.

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[1] 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 NBS also does not ask directly about individual or workforce human capital. To deal with this, and to generate relevant area-level controls, I use detailed small-area level workforce and demographic information from the Annual Population Survey (APS), which contains a boosted local sample that allows for reliable sub-regional estimates.[2]

More broadly, innovation survey data has pros and cons. It avoids some of the constraints in patents analysis, such as manufacturing skew, vulnerability to policy / industry shocks and lack of explicit quality measure (OECD, 2009). On the other hand, surveys risk a response bias towards innovating firms and may capture trivial developments (Smith, 2005). The NBS deals with the first issue through careful sampling and with the second through focusing explicitly on 'new innovations'; this may be easier to identify for new products than for new processes.[3]

3.1 Key variables

Business turnover information is simply organised into seven bands, ranging from 'up to £49,000 / year' to '£5m+ / year'.[4] I use the midpoints of these bands (£25,000, £75,000, £125,000 and so on) to fuzzily illustrate effect sizes from changes in the independent variable, TMT diversity. Building on Ottaviano et al (2007), I construct a linear measure of TMT diversity based on the

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[2] 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.

[3] The precise wording is: " Has your business introduced a new product or process innovation in the last 12 months? And do you expect to introduce a new product or process innovation in the next 12 months?"

[4] 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+).

underlying shares of minority ethnic and female team members. The variable is 'folded' to take a maximum value of 0.5, corresponding to maximum evenness in the underlying groups in firm i:

$$DIV_i = 0.5 - | SHARE_i - 0.5 |$$ (1)

DIV has a minimum value of 0 (corresponding to $SHARE$ of 0 or 1, homogeneity); when the underlying minority/female share is 0.25 or 0.75, DIV takes the value 0.25. It is of course possible that (say) 25% and 75% female TMTs are qualitatively different. Also, these diversity measures say nothing about *types* of TMT homogeneity. In a second stage I unpack these issues by fitting dummies for all-male/female and all-minority/majority TMTs.

Testing for non-linearity is not straightforward. In the NBS data the majority of firms have non-diverse TMTs – for example, the average share of minority TMT members is under 4% (see Table 1). That implies a conventional polynomial may be hard to fit. Alongside the linear measure, therefore, I fit a dummy taking the value 1 if the TMT has any heterogeneity. This allows me to separate a) the 'effect' of at least some TMT 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. For gender diversity I am also run regressions with a quadratic term.

3.2. Descriptives

Table 1 provides summary statistics. Average turnover is between £100-499k (corresponding to the '3' band in the data). Firm TMTs are notably non-diverse in ethnicity terms, with the average

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top team having 3.5% minority ethnic members and 2.8% of firms with all-minority TMTs. Firms are more diverse in gender terms, with an average of 25% female representation on the TMT and just over 10% of firms with all-female top teams. Table A1 in Appendix 1 provides a correlation matrix for these main variables. This shows negative (simple, pairwise) correlations between TMT minority/female *shares* and turnover, but positive diversity-turnover links, which are significant at 5% for both ethnicity and gender.

Table 1 about here

The average firm is 6-9 years old (banded '3' in the data) and has around 20 staff outside the TMT (the largest firm having over 12,000 employees). Almost 75% of firms are independents; fairly few are exporters or use foreign inputs; around a third have a formal business growth plan or provided training to staff in the past year. Around a quarter report some product or process innovation in the last year; nearly 2/3 expect to invest in R&D in the coming year; but only a minority have formalised 'innovation links' to universities or through specialist networks.

4. Identification

Identifying causal effects of team characteristics on firm-level outcomes throws up a number of challenges that will bias OLS coefficients. First, we need to control for wider contextual or area-specific factors that may drive firm outcomes – for example, a technology shock might simultaneously raise firm performance and change TMT demographics (say, if firms seek to

recruit experts in that technology). We also need to be able to cleanly pick out area-level characteristics of interest. Second, we need to separate senior team characteristics from those of individual members, and the wider firm, characteristics not always observable (Adams et al., 2010). Both of these issues lead to spurious correlations if not dealt with.

Third, we need to deal with simultaneity, at both area and firm levels. Successful firms may select into the largest markets, which *ceteris paribus* will tend to have larger and more diverse populations. Not controlling for this leads up to (likely) upward bias in diversity coefficients (Card, 2010). Similarly, 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., 2013; Parrotta et al., 2014b).

4.1 Identification strategy

The cross-sectional nature of my data means that within-firm selection issues cannot be eliminated. I partially control for area-level selection using historic area-level demographic information, but am unable to instrument for these or exploit an exogenous shifter. The analysis therefore provides associations, rather than causal effects: the identification strategy is then to render these linkages as cleanly as possible.

I deal with observables using a combination of firm-level controls, plus industry and area fixed effects that handle sector context and time-invariant area characteristics. I test alternative urban

hierarchy measures to identify capital / core city interactions. I also select an analysis year, 2008, in which turnover-boosting external shocks are unlikely to occur or have occurred in years immediately preceding.

To tackle unobservables at firm level, I build on the approach of Ozgen and De Graaff (2013) and use Finite Mixture Modelling (FMM). FMM is a type of latent class estimation that is essentially a variant on unsupervised machine learning techniques (Hastie et al., 2009). Learning routines are computationally intensive and have only recently become popular, particularly in Big Data settings (Varian, 2014). FMM has been used in a range of science and social science fields, as well as a few cases in economics and the social sciences (Heckman and Singer, 1984; Baum-Snow and Pavan, 2012; Brown et al., 2014).

FMM provides a natural representation of unobserved heterogeneity by probabilistically splitting the sample into a number of homogenous latent classes or 'components' (Deb, 2008). The 'mixture' of classes is estimated semi-parametrically as multinomial logit probabilities in maximum likelihood: the same statistical model applies, but each class has different parameters of the distribution, allowing explanatory variables to have differing effects across components (Brown et al., 2014). The distribution of the dependent variable is typically used to specify likely densities. In this case business turnover is roughly normally distributed (see Figure 1), so the model is estimated as a 'mixture of normals'.

Figure 1 about here

The FMM estimator solves iteratively for models based on 2, … C latent classes, with the optimal model determined through model selection and actual convergence. Increasing C mechanically improves model fit statistics, but models with many components are less parsimonious and more complicated to interpret (Heckman and Singer, 1984). I am able to achieve convergence for up to five components: Appendix 2 provides diagnostic tests for these different models. Given the relatively small sample, an additional concern is to minimise the number of components with under 100 observations, since modelling will be based on sparse information, inference may not be reliable and small classes may also be driven by outliers rather than group-homogenous characteristics (Deb, 2008). Overall, a three-component model best fits the distribution of turnover in Figure 1, with the biggest gains in model fit from smaller-component models, while still allowing for robust and parsimonious interpretation.

FMM estimation introduces additional complexity to the analysis, and as with all structural models, identification is not always straightforward compared to OLS (Angrist and Pischke, 2009). However, as Ozgen and De Graaff (2013) point out, in this case the FMM approach has a number of useful features: it allows endogenous assignment of observations to specific classes, and allows comparison of these sub-sample outcomes to average associations across the whole. It thus allows us to test whether diversity-turnover linkages differ across different groups of firms, and to explore the characteristics of those groups in some detail.[5]

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[5] Alternative candidate identification strategies would include a control function or a Heckman selection model. I have experimented with both of these approaches. 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.

5. Model and estimation

I fit a production function model for firm i in sector j and area a:

$$Y_{ija} = f(\textbf{EDIV}b_{ija}, \textbf{FDIV}c_{ija}, \textbf{CTRLS}d_{ija}, \textbf{CTRLS}e_a, J_j, A_a, u_{ija}) \qquad (2)$$

Where Y is banded turnover, **EDIV** is top management team ethnic diversity, 'folded' to a maximum of 0.5 as described in section 3.1, and **FDIV** is defined identically for TMT gender diversity. I fit both linear TMT diversity measures and the 'diversity dummy' in the main analysis. I interpret coefficients b and c as average marginal 'effects' (associations).

The controls vectors are populated from the existing business performance literature. Firm-level controls (**CTRLS**$dija$) include firm age, number of non-TMT employees, number of owners / partners, firm legal status, workforce development activity, growth plans and operating capacity. 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 is likely to influence performance, since subsidiaries benefit from both financial and informational resources from parent firms (Javorcik, 2004); such corporate structures may also influence TMT choices. I thus fit dummies for UK subsidiaries, foreign subsidiaries, ultimate holding companies, independents and LLPs, with 'unknown' the reference category.

Firms' human capital, whether in the workforce or in management may turn out to explain apparent TMT 'effects' (Parrotta et al., 2014a). To get an approximate fix on firms' human

capital I fit dummies for whether firms have attempted to improve their skills base through training (no training being the reference category); in robustness checks I complement this with area-level skilled workforce measures. Similarly, 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.

Crucially, the area-level vector **CTRLS**ea provides partial controls for area-level conditions that may affect both firm performance and TMT demographics. Urban location helps firms to become more productive via agglomeration economies, raising turnover (Rosenthal and Strange, 2004); urban areas also tend to have more diverse populations, which may influence top team characteristics. To control for this I fit the natural log of NUTS2 population density, lagged to 2001. TMT characteristics may collapse to other characteristics of the wider area population too; besides population density, I also fit controls for a given area's minority ethnic population share in 2001. Finally, J and A represent one-digit industry and NUTS2 fixed effects. Standard errors are clustered on SIC1.

I estimate FMM results with maximum likelihood. For comparison I run OLS regressions on the whole sample, for direct comparison of average marginal 'effects' and those for latent classes.[6]

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[6] A potential alternative estimator to OLS would be an ordered logit, given that turnover is strictly banded rather than continuous. However, each band is quantified so this approach is less appealing in practice, and the required proportional odds assumption may not hold.

6. Descriptive analysis

Table 2 provides diagnostic information that summarises the 'performance' of the three-component FMM model, drawing on the tests described in Appendix 2.

Table 2 about here

The top panel provides the classification of subjects based on posterior probabilities, which specify the probability that firm i belongs to class C given that we observe firm turnover: these comprise 28.8%, 58.2% and 19.9% of the sample. The middle panel shows average posterior probabilities for each class: that is, the underlying probability of a firm assigned to C1 truly being in C1. This suggests assignment is fairly clean, ranging from 0.729 to 0.887. The bottom panel presents a range of model fit statistics. Entropy is of particular interest, and ranges from 0 (every firm has an equal posterior probability of membership in all classes) to 1 (each firm has posterior probability 1 in a given class). Here, the entropy score of 0.574 suggests assignment is significantly better than random. Log-likelihood for FMM models is substantially better than in OLS regressions (see Table 5).

6.1 Characteristics of the latent classes

Table 3 summarises the mean characteristics of the pooled sample and each of the latent classes. As the latter are probabilistic, rather than observed, I also provide a class-weighted average

measure. This gives the implied sample average, and functions as a further crosscheck on the modelling: the closeness of the modelled and observed sample means is reassuring.

The top panel of Table 3 compares components according to the variables of interest and controls. Overall, C1 firms emerge as the largest, most successful in turnover terms and most formalised in terms of structures and workflows. Component 1 firms have the highest turnover by some way (over £500k), with component 2 firms in the middle (£100-499k) and component 3 firms the lowest, at under £100k on average. However, component 3 firms have the highest minority ethnic and female TMT shares, and the greatest incidence of all-minority / all-female TMTs. Component 1 firms are much larger than those in other components, with over 62 staff (compared to 7 and 4 for C2 and C3 respectively). By contrast, there seem to be few age differences between classes. Component 1 firms are the least likely to be independent, although shares are high across all classes; component 1 firms are also the most likely to have a formal growth plan; to have trained staff; and to have formal linkages for R&D and information gathering. On each of these, C1 is followed by C2 with C3 firms being the least likely to have those characteristics.

The second panel gives industry breakdowns at SIC1 level. Component 1 firms are orientated towards manufacturing, distribution and public /personal services compared to the weighted average, component 2 towards hotels / catering and financial intermediation. Component 3 is

similar to component 2 but with more of a skew: this class also has the highest share of primary industries.

The bottom panel gives the basic spatial distribution of the classes, using a Eurostat four-fold typology of city-regions. More than 2/3 of firms are in some kind of urban area, both overall and within classes. This broad urban orientation is highest for C1 firms, as is the 'big city' orientation (capital cities and second tier metros). On this basis, C3 firms seem the least urbanised. However, city-regions typically encompass multiple NUTS2 areas. Table A1.2 provides finer-grained analysis at NUTS2 level: this shows that C3 firms have the highest representation in Inner and Outer London, with C2 firms in the middle and C1 firms least London-based.

7. Regression analysis

This section sets out the main results of the regression analysis. I begin with simple OLS results, comparing these to FMM regressions. I then run a number of robustness checks.

Table 4 sets out the results from the FMM regressions, with OLS coefficients given for comparison. In each case, column 1 fits EDIV alone, column 2 FDIV alone and column 3 both together. The top panel fits the linear diversity measure. Recall that pairwise correlations suggest positive links between DIV and business turnover. For ethnic diversity, these basic links survive adding controls, with the OLS coefficient of EDIV 1.070 significant at 5% (column 3). By contrast, coefficients of FDIV are non-significant. A 10% increase in EDIV thus implies a 10.7%

rise in turnover. For a firm in turnover band 3 (midpoint £250k), this equates to a rise in turnover of £26,750.

Table 4 about here

As in Ozgen and De Graaff (2013) the FMM results are also substantially different from those in the pooled sample, highlighting the importance of controlling for unobservables. Coefficients of EDIV shift depending on the model fitted; in the fullest specification (column 3) we find a strong positive link for C1 firms (1.706) and a much smaller link for C3 (0.180), both significant at 1%. Coefficients of FDIV are consistently positive for C3 (0.219 in the fullest model, significant at 1%), but are unstable for C1 and C2.

The bottom panel of Table 5 adds the diversity dummy to proxy for non-linearity. Here, EDIV becomes non-significant in the OLS results. By contrast, FDIV results strongly suggest an N-shaped relationship rather than a linear link. The FMM approach disentangles some of the underlying linkages. For EDIV, C3 firms show signs of a U-shaped relationship, significant at 1%. Specifically, results from the fullest model (column 6) suggest that for C3 firms, an ethnically diverse TMT is linked to a 0.984 percentage point drop in turnover compared to a homogenous firm, equivalent to a £738 drop for the average C3 business (whose average turnover band has a midpoint of £75,000). However, a 10% rise in TMT diversity after this brings a 15.83% rise in turnover, worth approximately £11,800 to a C3 firm. This U-shape relationship is much weaker for C1 and C2 firms, with the former showing non-significant

coefficients of EDIV when fitted alone (column 4) and a linear relationship when fitted with FDIV (column 6).

For gender diversity, the results suggest that the N-shape link exists for C2 and C3 firms, but not for C1. Table A1.3 explores this further by fitting a quadratic model. This confirms a significant N-shape link for C2 and C3 firms, significant at 1%, although coefficients on the quadratic blow up a little. Turning points are respectively 0.10 and 0.11 on the folded diversity measure, which corresponds to underlying female TMT shares of 20% and 21%. For C1 firms, coefficient point to an N-shape relationship but are not significant.

Overall, we see that different 'diversities' have varying relationships to firms' turnover, and to each other. Pooled results also hide substantial differences in size and sign between groups of firms. C1 firms, the largest and most established, have a positive linear link from ethnic TMT diversity to turnover, but show no gender TMT links. C2 firms show no ethnicity links but an N-shaped relationship for gender. C3 firms, the smallest, most financial services-based and most London-centric group, show positive linear linkages on both ethnicity and gender, and also show some evidence of non-linear relationships (U-shaped for ethnicity, N-shaped for gender).

7.1 Robustness checks

Table 5 runs through a series of robustness checks. Main FMM results are provided in Column 1 for reference: OLS results are available on request.

Table 5 about here

First, Column 2 removes London observations from the model (around 5.6% of all observations). While OLS coefficients barely change, FMM results shift substantially with particularly large shifts in size and sign for EDIV coefficients. Taken at face value, this suggests that for firms in a given class, TMT ethnic diversity plays in opposite directions depending whether or not they are located in the capital or not. Section 8 explores this further by looking at the interaction of TMT-level diversity with area type and demographics.

The NBS does not contain information on firm-level human capital, which is a potentially important omitted variable in equation (2). Columns 3 and 4 fit alternative area-level human capital measures taken from the UK Annual Population Survey. As expected, these shift coefficients of EDIV and FDIV, but the overall distribution of results remains the same.

Next, Column 5 fits additional controls for innovative activity, specifically whether firms expect to invest in R&D, have university-industry links or use professional networks. Including these controls changes the main results, but on a much smaller and sample – so direct comparisons are hard. Column 6 includes the banded share of exports, reflecting the well-known link between exporting and firm performance (Wagner, 2007). Coefficients of EDIV are reduced for C1 and C3 firms, becoming insignificant in the latter case. By contrast, FDIV becomes significant for C2 firms. Other research shows positive connections between diversity and trade, so the latter may be an intervening variable in diversity-turnover links (Docquier and Rapoport, 2012). Here, regressing exports on EDIV turns up an OLS coefficient of 1.091, significant at 5%; for imports

this is 1.012, significant at 10% (for gender diversity, links is non-significant). For both innovation and exports, then, the analysis raises broader questions about the linkages between diversity, innovation, trade and business performance that need to be addressed further in other research.

Finally, I re-run equation (2) using two-way clustering on standard errors to deal with error correlation across (non-nested) industries and geographies. Following techniques developed by Cameron et al (2011), Table A1.4 compares OLS estimates with and without two-way clustering. Results barely change, suggesting that local industry shocks are not driving the main findings.

8. Extensions

8.1 Ethnic diversity, firms and cities

As discussed in section 2, in theory urban location might amplify links from firm-level ethnic diversity to business performance, through urban demographics and/or the productivity-enhancing role of cities. For this data, the robustness checks in Section 7 certainly suggest that London location shapes overall results.

I use the Eurostat city-regional typology to explore these issues further. First, I fit dummies for capital city-region and second-tier city-region location, and interact these with TMT ethnic diversity in equation (2). With lagged area-level demographics in the controls vector, this

specification should highlight any productivity-enhancing role of urban areas. Results for London and surrounds are set out in Table 6 (top panel).

Table 6 about here

OLS results show a positive significant effect of capital city location (column 1). Notably, for C3 firms this is negative significant, and turns EDIV negative too. Fitting the interaction shows a partial effect of 1.926 in the OLS, significant at 10% (column 2). This appears to be driven by C3 firms, where the partial effect is 1.075, again significant at 10%. For these firms, the total effect of EDIV is 1.207, and is increasing in capital city-region location, versus 0.132 for C3 firms in other city-regions; this suggests some amplifying effect of London and surrounds for these businesses, but the link is relatively weak.

Next, I make a three-way interaction between TMT diversity, lagged area-level diversity and urban type. Results are shown in the bottom panel. Comparing the size/sign of these partial and total effects with the previous estimates helps test whether urban demography also plays a role in city 'effects'. OLS results give an insignificant partial effect of EDIV, and a total effect driven by TMT diversity rather than area-level characteristics. By contrast, FMM results show partial effects for C2 and C3 firms significant at 1%, with a total effect of EDIV for C3 businesses that is increasing in location as before. In this case, the total effect of EDIV in the London city region (EDIV*location*demography) is smaller than EDIV*location alone (0.66 vs. 1.207) but more robust (1% vs. 10% significant).

In Table A1.5, I re-run these regressions for second tier metro city-regions. Here, partial effects are interpreted as the relative 'effect' of EDIV in a second tier location, relative to all other locations (including the capital and surrounds). As before, the top panel shows the EDIV*location interaction, and the bottom panel shows EDIV*location*demography. Partial effects of EDIV*location are negative and non-significant in the OLS, weakly positive significant for C1 firms and non-significant for C2 and C3 firms. Overall, and in all FMM classes, total effects of EDIV are decreasing in second-tier cities – in clear contrast to the capital city-region results.

For EDIV*location*demography, partial effects are positive significant for C3 firms, and non-significant for other classes and OLS results. As with diversity-location interaction, total effects are always decreasing in second tier locations. Alternative specifications using a combined capital and second-tier city-region location dummy also find declining total effects of EDIV for C2 and C3 firms (results are available on request). Together, these results suggest that second-tier locations lack the amplifying effects on firm diversity present in the London city-region, either through agglomeration economies or demography.

Overall, these results suggest that firm-level diversity-turnover links are amplified in the London city-region, but not in other metros; that both agglomeration economies and demographics play a role; and that 'effects' are driven by C3 firms, which are smallest, youngest and most service-orientated (and most London-based). This is consistent with the 'nursery cities' hypothesis that smaller, younger firms benefit most from big city learning effects (Jacobs, 1961; Duranton and

Puga, 2001). These results are also consistent with Trax et al (2012), who find that area-level diversity is at least as important to firm performance as internal workforce composition.

8.2 Homogeneity analysis

As a final extension of the analysis, I re-run equation (2) using dummies for homogenous TMTs instead of the linear diversity measure. Specifically, for ethnicity I fit dummies for all-majority and all-minority TMTs; and for gender, all-male/female TMTs. In both cases associations are interpreted as the relative 'effect' of that TMT composition versus diverse firms. As discussed in Section 3, this approach helps uncover the *kind* of homogeneity linked to turnover, and what homogeneity payoffs / penalties might exist. Results are given in Table A1.6: the top panel looks at ethnicity and the bottom panel gender.

Pairwise correlations in Table A1.1 suggest negative links from all-minority and all-female TMTs to turnover in the pooled sample. These hold up in the OLS analysis: I also find smaller, negative significant links from all-majority TMTs, but there is a non-significant and close to zero link from all-male TMTs. A priori, penalties from 'lock-in' should be similar for all homogenous groups, so that the larger penalties against all-minority and all-female headed firms imply the presence of external discrimination. However, the FMM analysis suggests some important within-sample differences. For ethnicity, C1 and C3 firms show similar results to the OLS, but C2 firms suggest positive links from homogeneity to turnover, which are 1% significant for all-minority TMTs. For gender, C1 firms show positive links from all-male TMTs; C2 firms replicate OLS results; while for C3 firms, all-male penalties are larger than all-female.

9. Discussion

This paper examines some current hot issues in the 'economics of diversity': firm-level links from diversity to business performance, and the interaction of firm and area-level characteristics, especially urban location. Unusually, my data allows me to focus the analysis on firms' 'top teams', who play a crucial role in setting the strategic direction of the business, and compares ethnic and gender diversity in the TMT. It is one of very few studies to do this. I also use latent class analysis to handle firm-level unobservables. This leads to substantial improvements in identification over OLS results, and highlights significant differences between groups of firms.

Overall, I find that ethnic and gender TMT diversity have varying relationships to firm turnover across firm classes, and relative to each other. The largest and most established firms in my data show a linear link from ethnic diversity to revenue; other groups, predominantly smaller and less formalised in working structures, seem to have non-linear relationships (U-shape for ethnic diversity, N-shape for gender). These hold most clearly for a group of the smallest, youngest, financial services and London-centric firms. This group also shows strong positive linear links from TMT ethnic and gender diversity. Strikingly, firms in this group based in London show some signs of amplified ethnic diversity linkages, via big city agglomeration economies and urban demography. By contrast, second tier metro locations exhibit decreasing effects.

There are some important caveats on these results. First, and crucially, my data is cross-sectional and so I am unable to control for firm-level selection effects. This means that the direction of causation is not clear, and results have to read purely as associations. This is common to firm-

level analysis of this kind: causation is very challenging to pin down (Adams et al., 2010). Second, the unavoidable banding of the outcome variable in the dataset reduces the precision of my estimates, and some controls are handled using workarounds.

As such, the analysis leaves a number of areas for further work. Worker-firm panel data, which is hard to construct in the UK, would substantially improve future research – not least by allowing researchers to test build and 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) for one example), so researchers tend to rely on lab studies or instruments. The external validity of the former is moot, especially given the urban context issues examined here. However, lab studies do highlight the importance of task and organisational context, which also appear to condition the impacts of group and firm demographics (Mannix and Neale, 2005). Similarly, gender / culture-specific individual preferences may also impact performance at the team level in ways that are hard to untangle in real world scenarios (Azmat and Petrongolo, Forthcoming). In situ research at this level 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.

kernel = epanechnikov, bandwidth = 0.2676
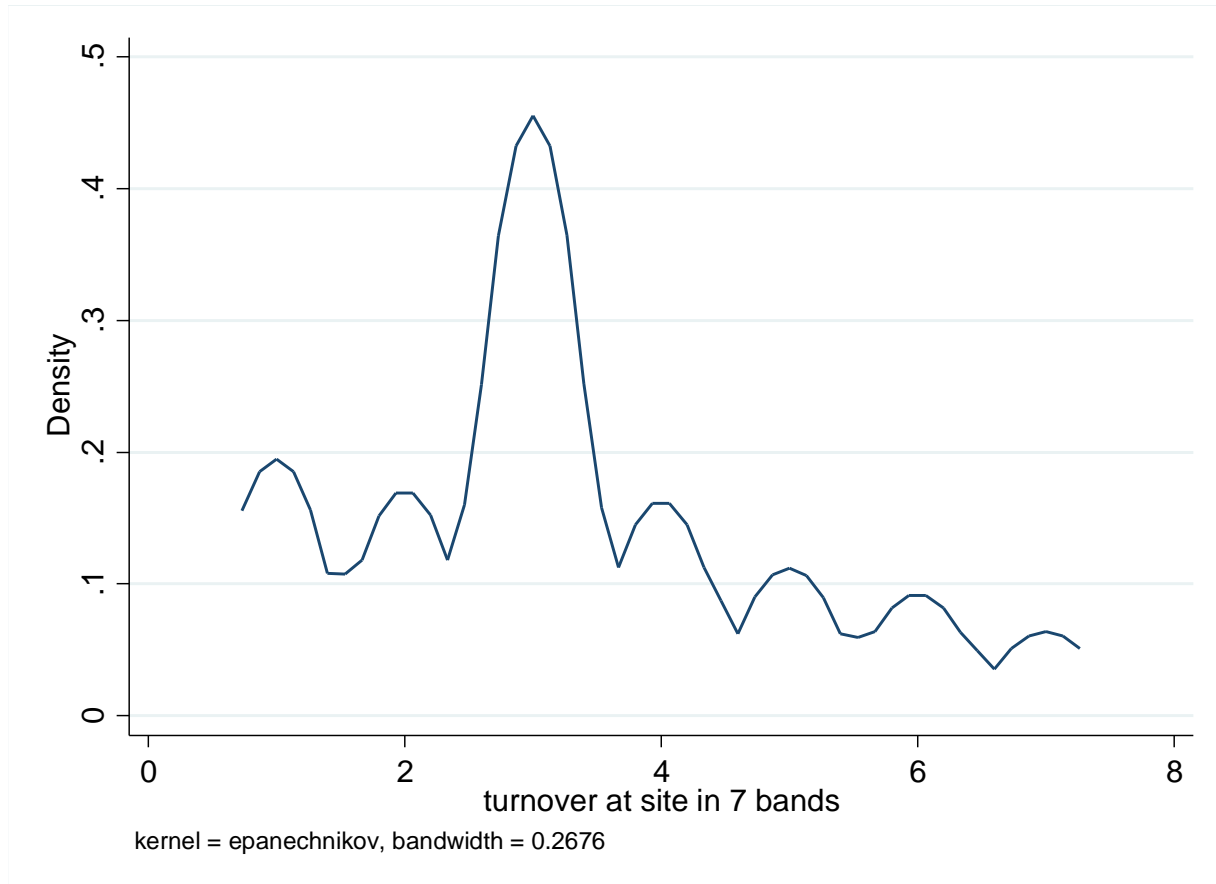
Source: RDA NBS.

Table 1. Summary statistics.

VARIABLES	N	Mean	SD	Min	Max
Turnover at site in 7 bands	2,381	3.297	1.628	1	7
% Minority ethnic TMT	2,381	0.0347	0.172	0	1
% Minority ethnic TMT folded	2,381	0.007	0.055	0	0.5
Minority ethnic-headed firm	2,381	0.028	0.164	0	1
% Female TMT	2,381	0.255	0.334	0	1
% Female TMT folded	2,381	0.148	0.218	0	0.5
All-female TMT	2,381	0.101	0.302	0	1
No of employees who receive a salary (excluding owners)	2,381	20.17	244.5	0	12,435
Number of owners/partners/directors	2,381	2.096	3.676	1	100
Years business in operation	2,381	3.397	0.858	1	4
Firm is subsidiary of UK parent	2,381	0.0326	0.178	0	1
Firm is subsidiary of foreign parent	2,381	0.0151	0.122	0	1
Firm is ultimate holding company	2,381	0.0138	0.117	0	1
Firm is independent	2,381	0.733	0.442	0	1
Firm is LLP	2,381	0.134	0.340	0	1
Share of foreign sales banded	2,381	0.696	1.444	0	6
Share of foreign inputs banded	2,381	1.018	1.804	0	6
Growth plan dummy	2,381	0.320	0.467	0	1
Business is operating below capacity	2,381	0.675	0.468	0	1
Hard-to-fill vacancies in past 12 months	2,381	1.813	0.390	1	2
Business provided some training in past 12 months	2,381	0.331	0.471	0	1
Product or process innovation in last 12 months	2,381	0.244	0.429	0	1
Firm expects to do R&D investment in next 12 months	2,381	0.621	0.485	0	1
Business uses U-I links for R&D	1,718	0.196	0.397	0	1
Business uses specialist networks for info	2,152	0.416	0.493	0	1
Ln(population density, 2001)	2,381	6.040	1.269	3.116	9.116
Five year lag of area minority ethnic working age population	2,381	7.032	9.095	0.500	41.75

Source: RDA NBS.

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Table 2. Three-component FMM performance.

Component	C1	C2	C3
Frequency	686	1386	309
Percent	28.81	58.21	12.98
Mean posterior probability	**Most likely latent class / component**		
	C1	**C2**	**C3**
p1	**0.887**	0.103	0.01
p2	0.253	**0.729**	0.018
p3	0.153	0.096	**0.751**
Entropy	0.574		
AIC	7039.985		
BIC	8021.782		
Sample size adjusted BIC	7481.656		
# free parameters	170		
Log likelihood	-3349.993		

Source: RDA NBS.

Table 3. FMM components: descriptive analysis.

Characteristic	Percentage of firms				
	All	**Comp 1**	**Comp 2**	**Comp 3**	*C1-3 weighted*
Turnover at site in 7 bands	3.297	4.491	3.124	1.913	*3.176*
% minority ethnic TMT	0.0347	0.034	0.035	0.048	*0.039*
% minority ethnic TMT folded	0.007	0.014	0.006	0.015	*0.012*
All minority-ethnic TMT	0.0275	0.020	0.029	0.045	*0.032*
% Female owners/partners/directors	0.255	0.246	0.259	0.276	*0.260*
% female TMT folded	0.148	0.144	0.154	0.144	*0.147*
All-female TMT	0.101	0.085	0.096	0.146	*0.109*
No of employees who receive a salary	20.17	62.67	7.25	4.38	*24.77*
Number of owners/partners/directors	2.096	2.376	2.085	2.003	*2.155*
Years business in operation	3.397	3.478	3.387	3.269	*3.378*
Firm is subsidiary of UK parent	0.0326	0.051	0.028	0.023	*0.034*
Firm is subsidiary of foreign parent	0.0151	0.028	0.010	0.013	*0.017*
Firm is ultimate holding company	0.0138	0.028	0.011	0.013	*0.017*
Firm is independent	0.733	0.726	0.741	0.761	*0.743*
Firm is LLP	0.134	0.118	0.149	0.091	*0.119*
Share of foreign inputs banded	1.018	1.108	0.911	0.906	*0.975*
Growth plan dummy	0.320	0.443	0.310	0.265	*0.339*
Business is operating below capacity	0.675	0.687	0.665	0.715	*0.689*
Hard-to-fill vacancies in past 12 months	1.813	1.748	1.832	1.867	*1.816*
Business provided some training	0.331	0.459	0.322	0.262	*0.348*
Product or process innovation	0.244	0.294	0.237	0.275	*0.269*
Firm expects to do R&D investment	0.621	0.685	0.617	0.599	*0.634*
Business uses U-I links for R&D	0.196	0.255	0.161	0.164	*0.193*
Business uses specialist networks for info	0.416	0.453	0.409	0.410	*0.424*
Primary (a-c)	2.45	1.60	2.45	3.56	*2.35*
Manufacturing (d-e)	12.5	15.31	11.54	11.97	*12.68*
Construction (f)	8.7	7.14	8.51	7.77	*8.02*
Distribution (g)	22.3	23.18	20.92	16.83	*21.04*
Hotels/catering (h)	6.52	4.23	6.93	9.39	*6.47*
Transport/storage/comms (i)	3.66	3.79	3.82	2.91	*3.70*
Financial intermediation (j-k)	35.04	32.22	37.95	42.72	*36.92*
Public/personal services (l-o)	8.83	12.54	7.86	4.85	*8.82*
Capital city region	13.77	15.31	15.44	14.24	*15.25*
Second tier metro region	20.02	24.93	21.72	21.36	*22.60*
Smaller metro region	29.12	27.99	27.92	30.42	*28.26*
Other regions	37.08	31.78	34.92	33.98	*33.89*
Observations	*2381*	*686*	*1386*	*309*	*2381*

Source: RDA NBS.

Table 4. Diversity and business turnover. Main results.

Depvar = turnover	(1)				(2)				(3)			
	OLS	C1	C2	C3	OLS	C1	C2	C3	OLS	C1	C2	C3
% Minority ethnic TMT folded	1.074**	-0.762	1.479***	-0.423***					1.070**	1.706***	-0.557	0.180***
	(0.335)	(0.770)	(0.535)	(0.111)					(0.336)	(0.589)	(0.372)	(0.004)
% Female TMT folded					0.060	0.265***	-0.632**	0.192***	0.054	-0.494**	0.093	0.219***
					(0.076)	(0.083)	(0.261)	(0.009)	(0.070)	(0.241)	(0.147)	(0.002)
Observations	2381		2381		2381	2381			2381	2381		
Log-Likelihood	-3975.964		-3334.279		-3978.558	-3280.209			-3975.868	-3221.92		

	(1)				(2)				(3)			
	OLS	C1	C2	C3	OLS	C1	C2	C3	OLS	C1	C2	C3
% Minority ethnic TMT folded	0.129	2.288	3.065*	2.587***					1.270	4.492**	0.863	1.583***
	(1.678)	(1.541)	(1.716)	(0.105)					(1.375)	(2.090)	(1.471)	(0.082)
Ethnic-diverse TMT dummy	0.420	-0.252	-1.367*	-1.279***					-0.152	-1.322	-0.648	-0.984***
	(0.702)	(0.674)	(0.721)	(0.048)					(0.611)	(0.871)	(0.628)	(0.031)
% Female TMT folded					-3.218***	-0.793	-1.861***	-1.148***	-3.200***	-0.881	-1.740***	-1.714***
					(0.329)	(0.683)	(0.265)	(0.004)	(0.343)	(0.694)	(0.150)	(0.024)
Gender-diverse TMT dummy					1.581***	0.180	1.031***	0.753***	1.570***	0.169	0.968***	0.977***
					(0.161)	(0.273)	(0.115)	(0.002)	(0.167)	(0.303)	(0.065)	(0.009)
Observations	2381		2381		2381	2381			2381	2381		
Log-Likelihood	-3975.687		-3313.681		-3953.309	-3218.39			-3951.207	-3267.289		

Source: RDA NBS.

Note. Controls include top team size, firm age, firm employees, firm type dummies, whether firm has hard to fill vacancies; has a growth plan; has provided internal/external training; has innovated in the past year; is operating below capacity. Area controls are population density and minority ethnic working age population, lagged to 2001. All models use SIC1 and NUTS2 dummies. HAC standard errors clustered on SIC1. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 5. Robustness checks.

Dependent variable	(1)			(2)		
= turnover	**C1**	**C2**	**C3**	**C1**	**C2**	**C3**
% Minority ethnic TMT folded	1.706***	-0.557	0.180***	-0.266	2.004***	-0.691***
	(0.589)	(0.372)	(0.004)	(0.615)	(0.629)	(0.010)
% Female TMT folded	-0.494**	0.093	0.219***	0.214*	-0.586***	0.429***
	(0.241)	(0.147)	(0.002)	(0.118)	(0.191)	(0.003)
London	Y	Y	Y	N	N	N
Observations		2381			2248	
Log-likelihood		-3221.920			-3060.192	
	(3)			**(4)**		
	C1	**C2**	**C3**	**C1**	**C2**	**C3**
% Minority ethnic TMT folded	1.886***	-0.124	0.151***	1.987***	-0.100	0.059***
	(0.675)	(0.378)	(0.045)	(0.751)	(0.519)	(0.002)
% Female TMT folded	-0.710***	0.301	0.350***	-0.592**	0.258*	0.243***
	(0.228)	(0.200)	(0.082)	(0.233)	(0.138)	(0.001)
% Area professionals	Y	Y	Y	N	N	N
% Area NVQ4	N	N	N	Y	Y	Y
Observations		2104			2104	
Log-likelihood		-2899.036			-2816.278	
	(5)			**(6)**		
	C1	**C2**	**C3**	**C1**	**C2**	**C3**
% Minority ethnic TMT folded	2.011**	-0.581	-0.483***	1.212***	-0.442	0.016
	(0.855)	(0.411)	(0.001)	(0.460)	(0.333)	(0.023)
% Female TMT folded	0.115	0.169	-0.376***	-0.412***	0.195***	0.137***
	(0.274)	(0.161)	(0.000)	(0.102)	(0.065)	(0.003)
Innovation controls	Y	Y	Y	N	N	N
% International sales	N	N	N	Y	Y	Y
Observations		1284			2381	
Log-likelihood		-1586.153			-3232.515	

Source: RDA NBS.

Note. Controls as in Table 4. All models use SIC1 and NUTS2 dummies. HAC standard errors clustered on SIC1. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 6. Ethnic diversity: linking firms, capital city-regions and urban demographics.

Dependent variable = turnover	(1)				(2)			
	OLS	C1	C2	C3	OLS	C1	C2	C3
% Minority ethnic TMT folded	1.088**	1.513**	-0.408	-0.573***	0.546	-0.150	0.578	0.132
	(0.327)	(0.624)	(0.256)	(0.003)	(0.460)	(0.691)	(0.383)	(0.228)
% Minority ethnic TMT * capital city region					1.962*	0.447	1.926	1.075*
					(0.981)	(0.640)	(1.539)	(0.567)
Capital city region	0.230*	0.131	0.114	-0.182***	0.207*	0.103	0.129	-0.024
	(0.114)	(0.227)	(0.094)	(0.001)	(0.103)	(0.128)	(0.289)	(0.114)
Observations	2381	2381			2381	2381		
Log-Likelihood	-3975.198	-3240.064			-3973.387	-3323.053		
	(3)				(4)			
	OLS	C1	C2	C3	OLS	C1	C2	C3
% Minority ethnic TMT folded	1.088**	1.513**	-0.408	-0.573***	0.853**	0.832**	-0.302	0.093
	(0.327)	(0.624)	(0.256)	(0.003)	(0.313)	(0.379)	(0.582)	(0.093)
TMT * capital CR * lagged minority population					0.048	-0.057	0.767***	0.567***
					(0.026)	(0.047)	(0.143)	(0.011)
Capital city region	0.230*	0.131	0.114	-0.182***	0.223*	0.151	0.162	-0.037
	(0.114)	(0.227)	(0.094)	(0.001)	(0.113)	(0.228)	(0.138)	(0.030)
Five year lag of area minority ethnic working age population	0.000	-0.002	0.004	0.007***	0.000	0.002	0.008*	0.002
	(0.003)	(0.012)	(0.003)	(0.000)	(0.003)	(0.009)	(0.004)	(0.001)
Observations	2381	2381			2381	2381		
Log-Likelihood	-3975.198	-3240.064			-3974.582	-3332.470		

Source: RDA NBS.

Note. Controls as in Table 4. 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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Appendix 1 / Additional results

Table A1.1 Correlation matrix of main variables.

	Turnover in 7 bands	% minority ethnic TMT	% minority ethnic TMT folded	All minority-ethnic TMT	% female TMT	% female TMT folded	All-female TMT
Turnover at site in 7 bands	1.000						
% minority ethnic TMT	-0.035*	1.000					
% minority ethnic TMT folded	0.043**	0.307***	1.000				
All minority-ethnic TMT	-0.053***	0.944***	-0.022	1.000			
% female TMT	-0.164***	-0.008	0.001	-0.009	1.000		
% female TMT folded	0.039**	0.002	0.043**	-0.013	0.456***	1.000	
All-female TMT	-0.214***	-0.013	-0.033*	-0.002	0.750***	-0.228***	1.000

Source: RDA NBS.

Note: * = pairwise correlation significant at 10%, ** 5%, *** 1%

Table A1.2 Firm latent classes by NUTS2 region.

NUTS2 region	Percentage of firms				
	All	**Comp 1**	**Comp 2**	**Comp 3**	*C1-3 weighted*
Tees valley and Durham	2.01	2.04	2.24	1.62	*2.10*
Northumberland and Tyne and Wear	2.71	3.5	2.53	2.27	*2.78*
Cumbria	1.15	1.46	0.87	1.29	*1.09*
Cheshire	1.56	1.46	1.59	1.62	*1.56*
Greater Manchester	2.27	1.75	2.53	2.27	*2.27*
Lancashire	2.08	2.04	1.95	2.91	*2.10*
Merseyside	0.85	1.17	0.94	0.65	*0.97*
East Riding and North Lincolnshire	6.05	7.14	6.06	4.53	*6.17*
North Yorkshire	6.35	5.83	6.93	5.83	*6.47*
South Yorkshire	4.42	5.39	4.04	5.5	*4.62*
West Yorkshire	8.35	8.75	8.59	7.77	*8.53*
Derbyshire and Nottinghamshire	7.91	7.43	7.58	10.03	*7.85*
Leicestershire, Rutland and Northampton	6.16	4.52	6.35	7.44	*5.96*
Lincolnshire	3.08	3.21	2.81	2.91	*2.94*
Hereford, Worcestershire and Warwickshire	2.23	1.9	1.73	3.88	*2.06*
Shropshire and Staffordshire	2.93	3.5	2.74	1.94	*2.86*
West Midlands	2.93	4.23	2.67	1.62	*2.98*
East Anglia	4.83	3.79	5.41	4.53	*4.83*
Bedfordshire and Hertfordshire	2.15	2.48	2.09	2.91	*2.31*
Essex	2.08	2.48	2.02	2.27	*2.18*
Inner London	2.82	2.77	2.81	2.91	*2.81*
Outer London	2.82	2.48	2.89	2.91	*2.77*
Berkshire, Bucks. and Oxfordshire	2.78	2.62	2.96	3.24	*2.90*
Surrey, East and West Sussex	4.12	3.5	4.55	3.88	*4.16*
Hampshire and Isle Of Wight	2.97	2.92	2.67	2.59	*2.73*
Kent	2.6	2.77	2.67	1.29	*2.52*
Gloucestershire, Wiltshire and N. Somerset	3.19	2.48	3.32	3.24	*3.07*
Dorset and Somerset	2.49	2.33	2.67	2.59	*2.56*
Cornwall and Isles Of Scilly	1.71	1.6	1.73	1.29	*1.64*
Devon	2.38	2.48	2.09	2.27	*2.23*
Observations	*2381*	*686*	*1386*	*309*	*2381*

Source: RDA NBS

Table A1.3. Turnover and gender diversity: quadratic model.

Depvar = banded turnover	(1)			
	OLS	**C1**	**C2**	**C3**
% Female TMT folded	2.307***	0.011	1.683***	1.477***
	(0.230)	(0.329)	(0.162)	(0.006)
(% Female TMT folded)^2	-13.192***	-2.718	-8.346***	-6.914***
	(1.334)	(1.960)	(1.053)	(0.043)
Gender-diverse TMT dummy				
Observations	2381	2381		
Log-Likelihood	-3950.679	-3249.294		
R^2	0.374			

Source: RDA NBS.

Note. Controls as in Table 4, plus folded % minority ethnic TMT. All models use SIC1 and NUTS2 dummies. HAC standard errors clustered on SIC1. Female TMT linear and quadratic terms are centred on the mean. * p<0.1, ** p<0.05, *** p<0.01

Table A1.4 Two-way clustering check, OLS model.

	(1) OLS	(2) CGMREG	(3) OLS	(4) CGMREG
% Minority ethnic TMT folded	1.070**	1.070***	1.270	1.270
	(0.336)	(0.253)	(1.375)	(1.391)
% Female TMT	0.054	0.054	-3.200***	-3.200***
	(0.070)	(0.106)	(0.343)	(0.475)
% Female TMT folded			-0.152	-0.152
			(0.611)	(0.631)
Gender-diverse TMT dummy			1.570***	1.570***
			(0.167)	(0.234)
Observations	2381	2381	2381	2381
R^2	0.361	0.361	0.374	0.374

Note. Controls as in Table 4. All models use SIC1 and NUTS2 dummies. HAC standard errors clustered on SIC1 (columns 1 and 3) and on SIC1*NUTS2 (columns 2 and 4). * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A1.5 Ethnic diversity: linking firms, second-tier metros and urban demographics.

Dependent variable = turnover	(1)				(2)			
	OLS	C1	C2	C3	OLS	C1	C2	C3
% Minority ethnic TMT folded	1.073**	-0.277	1.053	-0.242**	1.161**	-0.730	1.445**	-0.294
	(0.333)	(1.732)	(0.985)	(0.113)	(0.421)	(0.948)	(0.708)	(0.526)
% Minority ethnic TMT * second tier city-region					-0.417	0.983*	-1.015	1.681
					(1.416)	(0.505)	(0.875)	(2.300)
Second-tier city region	0.349**	0.371**	0.389***	-0.088***	0.350**	0.464*	0.301	-0.160***
	(0.151)	(0.181)	(0.124)	(0.033)	(0.152)	(0.237)	(0.353)	(0.045)
Observations	2381	2381			2381	2381		
Log-Likelihood	-3974.367	-3340.560			-3974.299	-3319.604		
	(3)				(4)			
	OLS	C1	C2	C3	OLS	C1	C2	C3
% Minority ethnic TMT folded	1.073**	-0.277	1.053	-0.242**	1.087**	1.566***	-0.479	-0.589***
	(0.333)	(1.732)	(0.985)	(0.113)	(0.370)	(0.512)	(0.470)	(0.003)
TMT * second-tier CR * minority pop					-0.006	-0.037	0.127	0.039***
					(0.095)	(0.042)	(0.125)	(0.000)
Second-tier city region	0.349**	0.371**	0.389***	-0.088***	0.349*	0.248	0.308*	-0.129***
	(0.151)	(0.181)	(0.124)	(0.033)	(0.152)	(0.243)	(0.164)	(0.001)
Lagged minority ethnic working age population	0.001	0.006*	0.002	-0.005**	0.001	-0.005	0.001	-0.009***
	(0.003)	(0.004)	(0.007)	(0.002)	(0.003)	(0.010)	(0.003)	(0.000)
Observations	2381	2381			2381	2381		
Log-Likelihood	-3974.367	-3340.560			-3974.365	-3218.532		

Source: RDA NBS.

Note. Controls as in Table 4. All models use SIC1 and NUTS2 dummies. HAC standard errors clustered on SIC1. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A1.6 Homogeneity analysis.

Dependent variable = turnover	(1)			
	OLS	C1	C2	C3
All minority-ethnic TMT	-0.775***	-1.278***	0.359***	-0.098***
	(0.156)	(0.347)	(0.129)	(0.001)
All majority-ethnic TMT	-0.456***	-0.595***	0.288*	-0.098***
	(0.133)	(0.214)	(0.170)	(0.001)
Observations	2381	2381		
Log-Likelihood	-3973.794	-3034.604		
R^2	0.362			

Dependent variable = turnover	(2)			
	OLS	C1	C2	C3
All-female TMT	-0.667***	-0.747***	-0.492***	-0.143***
	(0.044)	(0.115)	(0.069)	(0.001)
All-male TMT	-0.036	0.450***	-0.106*	-0.249***
	(0.044)	(0.144)	(0.060)	(0.001)
Observations	2381	2381		
Log-Likelihood	-3953.922	-3227.564		
R^2	0.373			

Source: RDA NBS.

Note. Controls as in Table 4. All models use SIC1 and NUTS2 dummies. HAC standard errors clustered on SIC1.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendix 2 / Finite Mixture Modelling diagnostics

I estimate a number of Finite Mixture (FMM) models, starting with the simplest two-component version. Convergence is possible up to five components, after which it becomes too fragile to be feasible in the analysis. I choose between models based on overall model fit statistics, component size, component precision and underlying fit to the dependent variable.

Table A2.1 compares overall model fit for the four models estimated. As expected, IC scores mechanically improve with each new component C, but for AIC, adjusted BIC and log-likelihood the magnitude of gain falls after four components. Entropy is a measure of the distinctiveness of each component, varying from 0 (everybody has an equal posterior probability of membership in all classes) to 1 (each individual has posterior probability 1 in given class) (Ramaswamy et al., 1993). Intuitively, entropy needs to be over 0.5 for interpretation to be feasible, suggesting at least three components are needed. Iterations required for convergence increase substantially from three to four components, and by an order of magnitude from four to five components.

Table A2.1 about here

Table A2.2 sets out estimated posterior probabilities, from the two-component model (top panel) to the five-component model (bottom). Standard deviations indicate the precision with which the estimator is able to assign observations to classes. Increasing C beyond three leads to some loss of precision in the two largest classes, but subsequent components are increasingly well-fitted.

Table A2.2 about here

Table A2.3 sets out the distribution of observations based on most likely class membership. For four and five-component models, some classes become 'small' in the sense that they have under 100 observations. Given the sample size, this could make inference dubious.

Table A2.3 about here

Table A2.4 gives the average posterior probabilities: these specify the probability that firm i belongs to class C given that we observe Yi, that firm's turnover. As with model fit, this also functions as an indicator of overall 'performance': scores need to be as close to one as possible for the given probability*component cell. Assignment into classes becomes cleaner as C increases. At the margin, is not clear that a five-component model provides overall gains above a four component model, with some classes becoming less precisely ascribed.

Table A2.4 about here

Taken together, these considerations suggest a three-component model is optimal, although a four-component model is also technically feasible. Figure A2.1 gives the density of the pooled sample against the four components.

Figure A2.1 about here

Appendix 2 / Figures and tables

Figure A2.1 Histogram / kernel density function, three-component model.
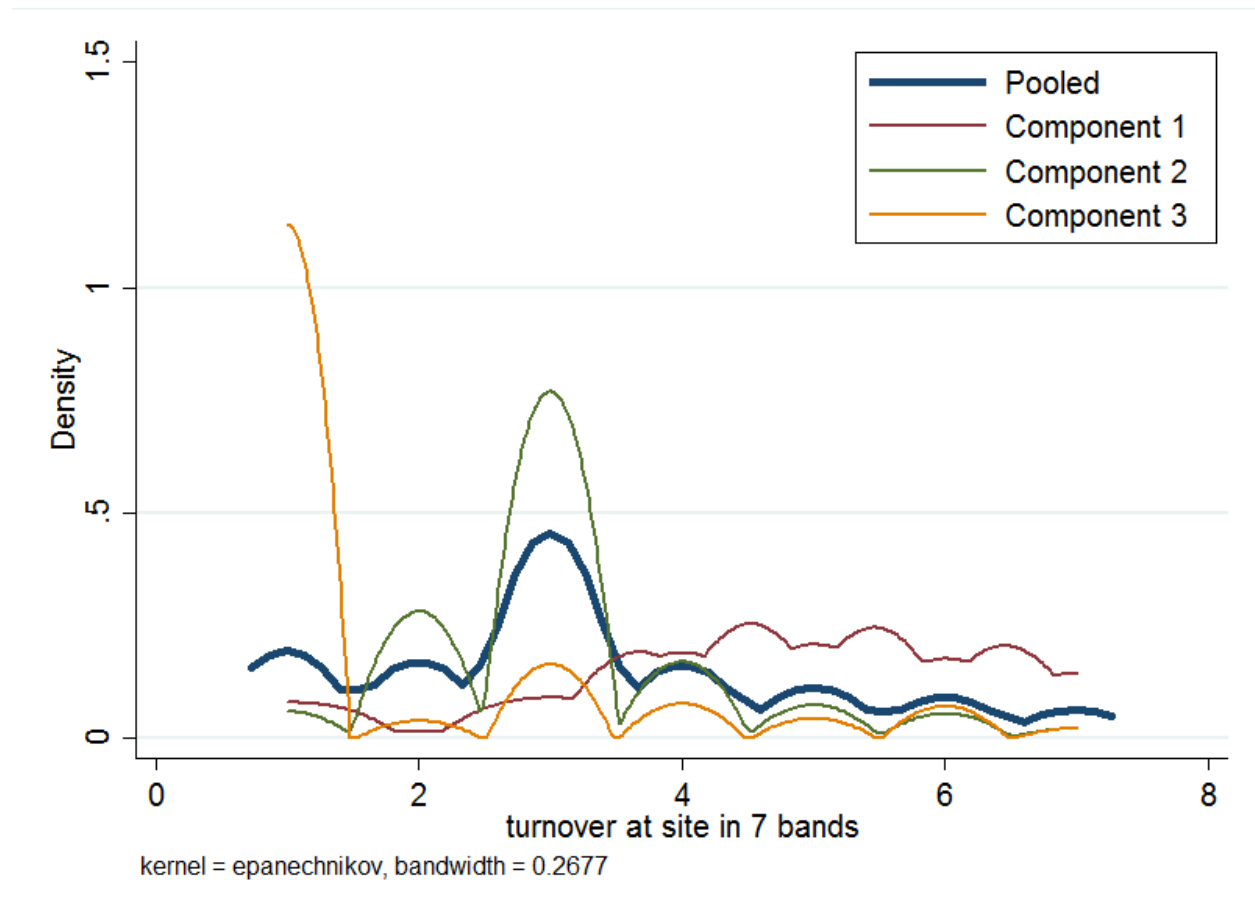
Source: RDA NBS.

Table A2.1 FMM model fit comparison.

Components	2	3	4	5
AIC	7234.696	7039.985	6612.435	6245.781
BIC	7887.302	8021.782	7923.423	7885.96
Sample size adjusted BIC	7528.277	7481.656	7202.195	6983.631
# free parameters	113	170	227	284
Log likelihood	-3504.348	-3349.993	-3079.217	-2838.891
Entropy	0.378	0.574	0.688	0.75
Iterations	19	38	98	1126

Source: RDA NBS.

Table A2.2 Estimated posterior probabilities.

Variable	Obs	Mean	Std. Dev.	Min	Max
post2_1	2381	0.310	0.273	0.000	1.000
post2_2	2381	0.690	0.273	0.000	1.000
post3_1	2381	0.437	0.328	0.000	1.000
post3_2	2381	0.450	0.338	0.000	1.000
post3_3	2381	0.112	0.264	0.000	0.998
post4_1	2381	0.460	0.342	0.000	1.000
post4_2	2381	0.407	0.340	0.000	1.000
post4_3	2381	0.099	0.258	0.000	0.999
post4_4	2381	0.034	0.179	0.000	1.000
post5_1	2381	0.482	0.349	0.000	1.000
post5_2	2381	0.377	0.336	0.000	1.000
post5_3	2381	0.073	0.236	0.000	1.000
post5_4	2381	0.032	0.175	0.000	1.000
post5_5	2381	0.036	0.179	0.000	1.000

Source: RDA NBS.

Table A2.3 Classification of subjects based on most likely latent class membership.

Component	Frequency	Percent
1	421	17.68
2	1960	82.32
1	742	31.16
2	1324	55.61
3	315	13.23
1	832	34.94
2	1183	49.69
3	283	11.89
4	83	3.49
1	916	38.47
2	1089	45.74
3	204	8.57
4	78	3.28
5	94	3.95
Total	*2381*	

Source: RDA NBS.

Table A2.4 Average posterior probabilities.

Average posterior probability	Most likely latent class				
	LC1	LC2	LC3	LC4	LC5
post2_1	0.835	0.165	.	.	.
post2_2	0.197	0.803	.	.	.
post3_1	0.887	0.103	0.01	.	.
post3_2	0.253	0.729	0.018	.	.
post3_3	0.153	0.096	0.751	.	.
post4_1	0.887	0.106	0.007	0	.
post4_2	0.266	0.723	0.01	0	.
post4_3	0.142	0.086	0.771	0	.
post4_4	0.01	0.016	0.001	0.973	.
post5_1	0.884	0.114	0.002	0	0
post5_2	0.282	0.715	0.002	0	0
post5_3	0.115	0.057	0.828	0	0
post5_4	0.007	0.009	0	0.984	0
post5_5	0.061	0.023	0	0	0.916

Source: RDA NBS.