SERC Spatial Economics Research Centre

SERC DISCUSSION PAPER 69

Does Cultural Diversity Help Innovation in Cities? Evidence from London Firms

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February 2011

This work is part of the research programme of the independent UK Spatial Economics Research Centre funded by the Economic and Social Research Council (ESRC), Department for Business, Innovation and Skills (BIS), the Department for Communities and Local Government (CLG), and the Welsh Assembly Government. The support of the funders is acknowledged. The views expressed are those of the authors and do not represent the views of the funders.

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Acknowledgements
Thanks to Riccardo Crescenzi, Ted Egan, Ian Gordon, Malo Hutson, Mark Kleinman, Jed Kolko, Max Neiman, Henry Overman, Andrés Rodríguez-Pose, Vivek Wadhwa, Kim Walesh and Peter Wood for comments and support. Participants at the 2010 AAG and SERC conferences, and an IURD Visiting Scholars' Roundtable at UC Berkeley provided helpful feedback. Thanks also to Matthew Waite at the London Development Agency for use of the London Annual Business Survey, and to Emma Drever for suggesting it. All errors and omissions remain our own.

Max Nathan is grateful to the ESRC and the Department of Communities and Local Government for research support. The views in this paper are the author's, and do not necessarily represent those of the Department or the ESRC.

Abstract
London is one of the world's major cities, and one of its most diverse. London's cultural diversity is widely seen as a social asset, but there is little hard evidence on its importance for the city's businesses. Theory and evidence suggest various links between urban cultural diversity and innovation, at individual, firm and urban level. This paper uses a sample of 7,400 firms to investigate, exploiting the natural experiment of A8 accession. The results, which are robust to most endogeneity challenges, suggest there is a small but significant 'diversity bonus' for London firms. Diverse management teams are particularly important for ideas generation, reaching international markets and serving London's cosmopolitan population.

JEL Classification: J61, L21, M13, O11, O31, R23
Keywords: cities, innovation, entrepreneurship, cultural diversity, migration, London

1. Introduction

Innovation is an important driver of long-term national economic growth and an important goal of policy intervention (Romer 1990, Schumpeter 1962). Cities and urban economic diversity enable innovative activity (Jaffe and Trajtenberg 1999, Duranton and Puga 2001). A growing body of evidence also suggests that *culturally* diverse cities are more innovative, as they benefit from a wider range of international knowledge links, diverse decision-making and being able to attract more innovative people (Hunt 2008, Peri 2007, Niebuhr 2006).

In theory, diversity-innovation effects largely operate at organisation level, but will be amplified in an urban context (Berliant and Fujita 2009). Yet no research has so far considered the impact of cultural diversity on innovation within firms in a highly diverse city. This paper looks at urban cultural diversity and innovation in detail, using a unique sample of 7,400 businesses in London. The UK capital is one of the world's major cities and one of its most culturally diverse – in terms of country of birth, language and ethnicity. London is substantially more diverse than 20 years ago: its cosmopolitanism is seen as a social asset. Does it help London firms to innovate?

Existing theory and evidence suggest a number of diversity-innovation channels. Culturally diverse teams may be better at generating new thinking or problem solving, particularly in knowledge-intensive environments (Page 2007, Fujita and Weber 2003). Through diasporic networks, migrant or minority staff and business owners can access additional upstream and downstream markets, assisting process innovation and the commercialisation of new ideas (Saxenian 2006). But diverse organisations may also have higher communication costs and lower trust, which will hold back innovation (Alesina and La Ferrara 2004).

More generally, 'ethnic entrepreneurs' are argued to play a number of critical roles in urban innovation. They are seen as more likely to develop new ideas (Wadhwa et al 2007, Stephan and Levin 2001), and can act as 'reputational intermediaries' between firms in different countries (Saxenian and Sabel 2008, Kapur and McHale 2005).

At city level, urbanisation economies may aid access to international markets;

conversely, large and diverse domestic markets provide more opportunities for product hybridisation (Mazzolari and Neumark 2009). In both cases diverse firms may be best placed to take advantage of these processes.

We use London as a test case for exploring these issues. We deploy data from London Annual Business Survey (LABS), using repeat cross-sections from 2005 to 2007. We exploit the survey's unique structure to look at links between the ownership characteristics of firms in London, the extent to which they innovate and their success in commercialising this innovation. We also make use of the unusual natural experiment conditions created by A8 accession in 2004, a policy shock that led to a large increase in net migration to the UK, and London in particular.

Our results suggest small but robust positive effects of management diversity on the development of new products and processes. In contrast to the wider literature, we find diversity-innovation effects across London's industrial structure. London's large and diverse home markets, diasporic communities and international connectivity play important roles, as do entrepreneurial migrant business owners.

Our results are robust to most endogeneity challenges, although the cross-sectional structure of the data means that firm-level reverse causation cannot fully be ruled out. Since this likely creates upward bias, our preference is to treat the main results as upper bounds. Overall, our findings suggest a small but significant 'diversity effect' and support claims that London's cultural diversity acts as an economic asset. As far as we know, these are new findings in a British context.

The paper is structured as follows. The next section sets out motivation and background for the research. Section 3 frames the ways in which urban cultural diversity may influence innovation. Sections 4 and 5 introduce data, descriptives and estimation strategy. Section 6 summarises our main results. Sections 7 and 8 set out extensions and robustness checks. Section 9 concludes and makes suggestions for further research.

2. Background and motivation

This paper asks the question: what effect, if any, does the cultural diversity of London's businesses have on their innovative activity? It looks at different aspects of diversity and innovation, focusing on the roles of management, owners and business partners in the capital.

2.1 Defining terms

Both 'cultural diversity' and 'innovation' are complex concepts and need careful definition. We follow the common definition of innovation as 'the successful exploitation of new ideas' (DIUS 2008). Innovative activity is generally held to involve both ideas generation and their commercialisation, both around new products and new processes (Fagerberg et al 2005). Individual entrepreneurs and entrepreneurial individuals within larger organisations are key to the innovation process (Schumpeter 1962). As a determinant of technical change and thus TFP, innovation is an important variable in overall national productivity: innovative firms' discoveries tend to permeate across the economy as a whole (Faggian and McCann 2009).

Cultural or ethnic diversity[1] is harder to pin down. It is a multifaceted concept, with subjective elements, and with categories that alter over time (ONS 2003). The key dimensions include kinship, religion, language, shared territory, nationality and appearance (Bullmer 1996). Group membership 'is something that is subjectively meaningful to the person concerned' (ONS 2003). And both culture and ethnicity are 'context-driven social and psychological concepts' whose meaning may shift as society evolves (Aspinall 2009).

For these reasons, attempts to quantify cultural diversity generally lose something in the process. We focus on two specific measures, country of birth and ethnic group, which are widely used in the literature as proxies for diversity generally. Country of birth has the advantage of being objective, but is one-dimensional and does not capture established minority communities. Ethnic groups attempt to combine different aspects of diversity, but operate at a very high level of generality (Mateos et al 2007). Ethnicity classifications also focus on classifying 'visible minorities' such as Black and Minority Ethnic (BME) groups,

[1] For the purposes of this paper, we use 'cultural diversity', 'ethnic diversity' and 'diversity' interchangeably.

without looking at ethnicity more broadly.

There are two potential problems with using these diversity proxies. First, if we believe identity is entirely self-ascribed, it becomes very hard to link behaviour to our measures (Casey and Dustmann 2009). This may affect measures based on ethnic groups, which are partly self-ascribed. However, it is difficult to think that (for example) commercial success might lead business owners of South Asian origin to identify as 'White British'. So we are relatively confident 'identity uncertainty' is not a major source of bias.

The second issue is that country of birth and ethnic group are distinct but overlapping: some migrants will be members of BME groups, and some recent minority communities may be largely non UK-born. In London the overlap is greater than in many other British cities. In the late 1990s and again from 2004, the UK experienced two large jumps in net migration. Many 'new migrant communities' have developed (Kyambi 2005). This means that the capital's current cultural diversity is largely driven by migrants from visible minorities, alongside groups captured in the 'other' category.[2] Table 1 shows the pairwise correlation between migrant and minority working-age population shares in Greater London is over 95%.

Bearing in mind the caveats above, we feel justified in using both country of birth and ethnic group as interchangeable proxies for London's cultural diversity. However, we highlight individual diversity channels likely to be specific to migrant or minority-ethnic groups and explore a number of migrant-specific processes.

2.2 Wider context

Links between diversity, cities and business success matter for policymakers, both in London and at national level. The UK's productivity gap with competitor countries – particularly the US – is an area of major policy concern. Innovation and entrepreneurship are two of the current Government's 'five drivers of productivity'; innovation is seen as particularly important (DIUS 2008). There is also a political consensus that growing diversity brings economic benefits, although there is disagreement about longer-term effects (HO / DWP

[2] In 2008, the 10 largest country of birth groups in UK cities were (in order of population share): Poland, India, Pakistan, Germany, Eire, Rep. South Africa, Zimbabwe, Bangladesh, USA (Nathan 2009).

2007, House of Lords Select Committee on Economic Affairs 2008). And while many business voices have embraced diversity, workplace discrimination is still a live issue (Golding 2009).

Urban areas also play a number of important roles. They are the locus of most people and economic activity (Parkinson et al 2006). Increasing returns in cities confer productivity payoffs and help support innovative activity (Overman and Rice 2008, Glaeser 2008, Audretsch and Feldman 2001). Urban areas are recognised as important to innovation at the national level in the UK (DIUS 2008), although the subsequent contribution of innovation to urban growth is less clear-cut (Christopherson and Clark 2007). British cities also contain the vast majority of the UK's migrant and minority populations (Champion 2006). Put simply, they are 'where the diversity is' (Nathan 2009).

London is our test case: it exemplifies the idea of the cosmopolitan world city. The UK capital is one of the original 'global cities' (Sassen 1991). Alongside New York, London remains a hub of the global financial system (Gordon et al 2009, Masters 2009). The capital dominates the UK economy: in 2006-7 it contained around 13% of the UK population but contributed nearly 20% of national GVA (Gordon et al 2007).

London is also one of the most culturally diverse cities on the planet. Over the past 15 years it has become substantially more cosmopolitan, both by receiving the majority of new UK migrants and via the emergence of settled new communities in the city. As Guardian journalist Leo Benedictus (2005) wrote in a recent survey:

> *London in 2005 is uncharted territory. Never have so many different kinds of people tried living together in the same place before. What some people see as the great experiment of multiculturalism will triumph or fail here.*

London's schoolchildren speak over 300 languages (Gordon et al 2007). In 2002-3 London accounted for around two thirds of English net migration; in 2001 the capital had over 48% of England's non-white population (Champion 2006). At least 50 'new migrant' communities with over 10,000 members live here (Benedictus 2005) The city's cultural diversity is widely seen as an economic strength, by national and city government as well as London's business community (DWP / HO 2007, GLA 2008, London First 2008). In particular, London's diversity is seen as driving forward ideas generation and the emergence of new products and services (Leadbeater 2008, Legrain 2006). London's service-dominated economy means that it performs poorly on traditional innovation metrics, such as R&D spending and patenting activity (Wilson 2007). So there is considerable interest in other aspects and drivers of innovative activity in the city.

3. Diversity, innovation and growth

Economic geography has seen increasing interest in the links between aspects of urban diversity and urban economic performance. A number of studies find that innovative activity is spatially concentrated, suggesting that cities and regions have an important role to play in fostering innovation by firms (Jaffe and Tratjenberg 1999, Zucker and Darby 1998). Spatial clustering seems to reflect localised knowledge spillovers (Storper and Venables 2004, Sabel and Piore 2001); sectoral composition (Griffith et al 2006); the presence of both very large firms and SMEs (Kelley and Helper 2001); and concentrations of skilled workers (Faggian and McCann 2009).

Economic diversity is related to urban innovation. Increasing returns in cities are linked to economically diverse environments (Glaeser et al 1992, Jacobs 1970); embryonic firms can benefit from diverse 'nursery cities' (Duranton and Puga 2001). There is also some suggestive evidence that cultural diversity plays a role in enabling innovation in urban areas. Peri (2007) finds that US states' share of foreign-born PhDs is positively associated with levels of patenting. Niebuhr (2006) finds a positive link between the diversity of German regions and regional innovation, with a stronger effect for the diversity of highly skilled employees. Hunt (2008) finds that immigrant population shares raise levels of patenting at the state level, and that state-level effects are greater than individual-level effects – suggesting some interaction between diversity, urban co-location and knowledge spillovers.

3.2 Diversity, innovation and cities

Diversity-innovation channels are likely to operate largely inside organisations. At the firm level, production complementarities and diaspora effects are likely to raise levels of innovative activity. Conversely, communication difficulties and discrimination will reduce organisations' ability to generate and commercialise new ideas. Diverse urban environments may amplify innovation activity, for example via population mix and home market effects (Berliant and Fujita 2009). 'Ethnic entrepreneurs' have a variety of important enabling roles in and around firms and cities, but make firm and urban level 'diversity effects' harder to identify: they may reduce to positive or negative selection at the individual level.

3.3 Diversity and innovation: firm-level processes

Teams: problem-solving, communication and trust

Diverse workforces may be more effective than homogenous workforces in problem solving or generating new ideas. 'Cognitively diverse' teams leverage a wider pool of perspectives and skills.[3] Crucially, cultural diversity is a good proxy for cognitive diversity (Page 2007).

Hong and Page (2004, 2001) show that in experiments with large teams of problem-solvers, the best problem-solvers often come up with similar solutions. So a diverse group may be preferable to a homogenous group, even if the latter have higher ability. These dynamics may be particularly important in research-based or knowledge-intensive activities (Fujita and Weber 2003). This has been modelled formally by Berliant and Fujita (2009) who show how in a system of firm-level knowledge creation worker heterogeneity can accelerates ideas generation through individual-level production complementarities. Diversity-performance effects may also be evident when new firms are founded. Evidence from the entrepreneurship literature suggests that team-based ventures tend to outperform firms with sole founders; conversely, ethnic homogeneity is one of the most powerful predictors of team formation, so diverse teams in young firms will be relatively rare (Hart 2010).

However, diverse teams may find it harder to communicate, and levels of trust may also be lower (Alesina and La Ferrara 2004). As a result, organisations may find it harder to make decisions or allocate resources, and the quality of those decisions may be lower than in more homogenous organisations. This will negatively affect both ideas generation and commercialisation activity.

[3] Page (2007) suggests that given a group of predictive models, the greater the diversity of modellers, the smaller the chances of error. This also implies that in some circumstances, the diversity of the problem- solving group is more important than individual talent.

Cultural diversity is thus good for team performance if its ongoing benefits outweigh initial disadvantages. Most recently, in a study of 165 Swiss firms, Nielsen finds that nationality mix in top management teams is linked to higher rates of foreign market entry and to higher firm profitability (Nielsen 2010, cited in Hart 2010). Hart analyses 24,000 'high-impact' US firms, finding suggestive evidence that team diversity is linked to employment (used here as a rough proxy for business success).

Wider reviews of the evidence find that there is a small but significant workplace 'diversity advantage' (Page 2007, Landry and Wood 2008). Negative communication and trust effects are often present in organisations, but are outweighed by positive effects of diversity over time (Page ibid). This implies that younger firms may find it harder to knit diverse teams together. As far as we are aware, no studies have yet tested firm-level diversity-innovation effects directly.

Diasporas, market access and innovation

Diverse workforces and management teams may have better access to international upstream and downstream markets, through leveraging diaspora social capital. In turn, that may foster innovation via changes to supply chains and production functions; opening up access to new consumer markets may also increase the demand for new products and services. Diasporas may reduce information and communication costs as knowledge is exchanged through groups with greater mutual understanding and trust (Rodríguez-Pose and Storper 2006). They also increase trust, and so facilitate supply chain links (Bresnahan and Gambardella 2005).

There is good evidence that diasporas can engage in innovative activity. Saxenian (2006) provides detailed evidence on the roles of migrant diasporas in Silicon Valley, which have strong links to production clusters in India, Taiwan and (increasingly) China. Similarly, Kapur and McHale (2005) detail the roles of diasporas in the development of ICT clusters in Ireland, Israel and South East Asia.

Discrimination

Migrant and minority-owned firms may face additional constraints in the marketplace. They may have greater difficulty in raising finance, for example, finding affordable space or developing client relationships. These reflect management and product quality, but may also be the result of lack of connections into mainstream economic institutions or discrimination (Gordon et al 2007). Lockout from particular markets may have little effect on ideas generation, but will make commercialisation harder. It is also likely to be a particular problem for minority-ethnic owned businesses.

3.4 City-level effects

There will also be city-level channels linking innovation and diversity, which may amplify the firm-level effects. For example, if cultural diversity contributes to economic diversity, it may help foster knowledge spillovers across sectors (Jacobs 1970). Specifically, diverse urban populations may demand a greater variety of goods and services, particularly in non-traded sectors. This will be driven both by the presence of new communities, and in some cases by shifting preferences in the majority population (Gordon et al 2007). The more cosmopolitan the environment, therefore, the greater the potential for hybridisation. In principle, there is no reason why any firm should not be able to take advantage of these opportunities. In practice, diverse firms may be better placed to spot and act on emerging opportunities.

A few studies have investigated these city-level effects. Immigration is positively associated with an increased range of restaurants in California (Mazzolari and Neumark 2009). And UK case studies have highlighted the role of migrant communities in the emergence of new sub-sectors of retail and leisure (Kitchin et al 2009, Jones et al 2004, Henry et al 2002).

3.5 'Ethnic entrepreneurs'

Schumpeter (1962) highlights the importance of 'the entrepreneurial function' in fostering innovation. Individual entrepreneurs push against social inertia, identifying and commercialising new ideas through new firm formation; 'collective entrepreneurship' in large organisations plays a similar function within the firm. Research on diversity and innovation places similar emphasis on so-called migrant or 'ethnic entrepreneurs'. Migration decisions reflect both expected returns and the taste for risk-taking. So migrants may be highly entrepreneurial, and more likely to look for and develop new ideas (Wadhwa et al

2007). Ethnic entrepreneurs can also act as ‘reputational intermediaries’, forging partnerships and helping markets access (Saxenian and Sabel 2008, Kapur and McHale 2005).

Empirical evidence on ethnic entrepreneurship is mixed. Some migrant and minority communities make disproportionate contributions to knowledge creation in US science and high-tech sectors (Stephan and Levin 2005). Migrants account for a disproportionate number of start-ups in US regions like Silicon Valley and the Raleigh-Durham Triangle (Wadhwa et al 2007, Saxenian and Sabel 2008). More prosaically, UK case studies have highlighted the role of migrant communities in retail and leisure hybridisation, as migrants create new products influenced by their backgrounds and tailored to the needs of particular groups (Kitchin et al 2009, Jones et al 2004, Henry et al 2002). But levels of self-employment seem to vary by migrant group, host country and class structure (Nakhaise et al 2009).

The phenomenon of ethnic entrepreneurship suggests a research focus on business owners and partners. But it also makes it harder to identify the specific role of *cities*: we need to test for positive and negative selection bias, in case diversity-innovation effects are actually explained by the individual characteristics of the entrepreneurs.

3.6 The 'Creative Class' and diversity

An alternative explanation for these results comes from ‘Creative Class’ theory (Florida 2002). Florida suggests that liberal, tolerant skilled workers are now the driving force of Western economies. This group is attracted to diverse firms and environments. The Creative Class is largely responsible for knowledge creation, so that culturally diverse firms will be more innovative – although diversity itself may no have direct effect. It is plausible that in a consciously cosmopolitan city like London, at least some of the workforce is deliberately seeking a diverse milieu. However, Creative Class approaches have been criticised for their theoretical foundations (e.g. Glaeser 2005), and appear to lose much of their predictive power in the UK (Nathan 2005).

4. Data and descriptives

Our main dataset is the London Annual Business Survey (LABS), an annual survey of firms conducted across the London region ('Greater London') by the London Development Agency. The questionnaire asks a range of questions covering firm formation, workforce and management characteristics, firm performance and constraints. Until very recently, the survey was the UK's only single firm-level source of information about organisational characteristics, business innovation and performance.[4]

In a previous paper we conducted preliminary analysis of 2007 LABS data (Lee and Nathan 2010). In this paper we improve the dataset in a number of ways. First, we pool together cross-sections from 2005-2007 inclusive. This allows us to significantly increase the sample size, to 7,425 firms. Second, although the sample is a repeated cross-section, we are able to use time-consistent industry codes to assemble year and industry fixed effects (at SIC3 level).[5] Both steps will improve the precision of our estimates. Third, we explore the natural experiment conditions created by A8 accession Effectively, London experienced an exogenous rise in diversity during the sample period. In 2004, eight Central and East European countries – joined the European Union. All member states apart from the UK and Sweden placed heavy restrictions on potential A8 migrants. The UK's decision not to impose entry restrictions was largely determined by political calculus (notoriously, studies at the time suggested entry numbers would be very small). However, the UK then experienced one of the largest increases in net migration since World War II, of which London received the lion's share (Economist 2006). Inflows began falling during the second half of 2008 as national economic conditions declined (ONS 2008).

LABS data allows us to explore diversity-innovation mechanisms in previously unavailable detail. However, focusing on London may limit the external validity of our results: the city's economy and demography are significantly different to other parts of the UK. We discuss this further in the concluding section.

[4] The LDA is one of nine Regional Development Agencies (RDAs) in England. The other RDAs now include questions about innovation in their annual business survey, which covers all nine regions. http://www.englandsrdas.com/

[5] We restrict the sample to SIC3 sectors represented in all three years. Sectors excluded include agriculture, forestry and hunting; fishing; mining and quarrying; and secondary manufacture related to these sectors, such as food processing.

4.1 Diversity measures

To get the most value out of the data, we construct a number of diversity measures from LABS' coverage of ownership characteristics, country of birth and ethnicity. Our two principle measures are dummies for the presence of migrant or minority ethnic owners/partners. *Migown* takes the value 0 if there are no non UK-born owners / partners, 1 if there is at least one migrant owner/partner. We also specify *migfirm*, which takes the value 1 if all owner/partners are non UK-born, and 0 if firms are not migrant-run. Our third measure, *ethown*, is derived from Q16a in LABS, 'whether at least half the owners are White British', and takes the value 1 if the answer is yes.

4.2 Innovation measures

We develop a number of innovation measures covering both ideas generation and commercialisation activities, and product and process innovations. Our first set of dependent variables cover four aspects of ideas generation. *Prodin1* is a dummy variable taking the value 1 if the firm has introduced a major new product or service in the past 12 months. Similarly, *prodin2* takes the value 1 if the firm has modified its product range or services during the year. *Procin1* takes the value 1 if the firm has introduced major new equipment in the past 12 months. *Procin2* measures whether or not the firm has introduced new ways of working during the year.

These variables cover important aspects of the innovation process – the introduction of new ideas – but take no account of whether implementation has been successful. For that reason, we also look at measures of commercialisation. A commonly used proxy for commercialisation is rapid revenue growth: innovation researchers define fast growing 'gazelle' companies as those achieving annual turnover growth of 20% or more (Council on Competitiveness 2005).

LABS provides limited turnover information in bands. We define 'gazelles' as firms in the sample that have achieved annual revenue growth of 10% or more. This is a weaker definition than is commonly used in the literature, and may reflect other factors feeding revenue growth (such as a change in tastes). To deal with this, we construct four dummy variables (*gprodin1*, *gprodin2*, *gprocin1*, *gprocin2*) that take the value 1 if firms have both introduced a new idea *and* seen annual revenue growth of at least 10%. Given the complex nature of much innovative activity in London, not many companies will be able to commercialise ideas at such a rapid rate.

4.4 Descriptives

Descriptive statistics are given in table 3. These show that around 25% of firms in the sample engaged in some kind of product or process innovation (for *prodin1*, around 30% of firms innovated). As expected, fewer firms were able to successfully commercialise new ideas (less than half the number who innovated around products or processes).

The diversity variables reflect London's rich people mix. Around 39% of firms in the sample have at least one foreign-born owner or partner, and around 22% have all migrant owner / partners. Of the firms with at least one migrant owner / partner, 59% are migrant-run. Around 21% of firms have at least half owners/partners from minority ethnic communities.

There is increasing interest in the 'knowledge economy', and the role of 'knowledge-based' firms in innovative activity. We deploy two principle measures of firm orientation. Our preferred measure is 'knowledge-intensive business services' or KIBS, which covers around 19% of the sample.[6] KIBS includes financial services, professional services, computer and data services, business services and technical services – sectors all well-represented in London, and which may account for a significant proportion of innovative activity (Wood 2006). As a cross-check we use The Work Foundation's definition of 'knowledge-intensive' and 'non-knowledge-intensive' firms, using (Brinkley 2008).[7] There are 3524 'knowledge-intensive' firms, around 48% of the sample.

[6] We use the definition of KIBS from Wood (2006). The mix of 3 and 4-digit SIC sectors 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.

[7] The Work Foundation follows the OECD definition of knowledge-intensive industries, but adjusts for the UK context (Brinkley 2008). The final list of 3-digit SIC sectors includes medium and high-tech manufacturing (pharmaceuticals, aerospace, computers and office machinery, electronic communications, software, other chemicals, non-electrical machinery, motors and transport equipment) plus a range of 'knowledge services' (post and telecoms, business services, finance, insurance, education, health, recreational and cultural activities).

Table 4 breaks down levels of innovation by firm type. As expected, in almost all cases knowledge intensive firms are more likely than average, and more likely than non-knowledge intensive firms to engage in ideas generation. Knowledge intensive firms are also slightly more likely to successfully commercialise their ideas.

5. Estimation strategy

We develop a simplified firm-level knowledge production function, linking the probability of innovative activity occurring to a diversity measure, firm-level controls, industry and year effects. For firm *i* in year *t*, we estimate:

$$Pr(Y_{it} = 1) = aDIV_{it} + \boldsymbol{CONTROLS_{it}b} + SECTOR_i + YEAR_t + e_i \qquad (1)$$

Y is variously one of our measures of ideas generation or commercialisation, as described above; DIV is the variable of interest, and is either a measure of migrant or minority owners/partners (*migown* and *ethown*), or a measure of management team composition (*divteam* or *migfirm*). DIV is intended to reflect the mix of individual, firm and city-level diversity-innovation effects that may be operating in London. SECTOR and YEAR are dummies for SIC3 sectors and years, respectively.

Controls are selected to reflect the literature on firm-level innovation. Levels and types of innovation are also likely to vary by sector: this is accounted for via sectoral fixed effects, and an additional dummy which takes the value 1 if a firm is part of the knowledge-intensive business services sector (KIBS).

Large or established firms often generate large amounts of patent activity, but small, often new firms may introduce disruptive innovations (Griffith et al 2006). Following initial diagnostics, we fit the log of age, and the log and square root of firm size. We also fit a dummy for company type: firms that are Public Limited Companies (PLCs) may be more innovative since they need to satisfy shareholder value.

We complete the model with dummies for exports, collaborative activity and R&D spending, plus further controls for human capital and management ability. There is an established literature on 'open innovation' and collaboration (Von Hippel 2005); equally, the role of R&D in innovation is well established (Romer 1990).

Unfortunately LABS has no information on workforce human capital (such as the share of a firm's employees with higher educational qualifications).[8] However, the survey provides detailed information on management experience and qualifications (dummies for previous experience, formal qualifications, on-the-job training, completion of management course). We fit all four measures as controls for management ability.[9] All should be positively correlated with innovative activity.

We estimate the model as a conditional logit model in Stata (using clogit). This estimator allows data to be grouped by sector, so better handles sector-specific, time-invariant effects. All specifications use HAC standard errors clustered on SIC3 sector. Initial diagnostics suggest a small number of outlier firms: removing the outliers makes little difference to the results, which are not reported here (output is available on request). As a further check we also run the model for both knowledge intensive and non-knowledge intensive firms.

5.1 Validity challenges

As noted earlier, using London-only data may limit external validity – an issue we return to at the end of the paper. There are also a number of potential internal validity challenges, First, an apparent diversity effect might turn out to be something else, such as human capital or sectoral characteristics (Glaeser 2005). We deal with this through careful model specification (in these two instances, four distinct human capital controls and a complete set of three-digit sectoral dummies). Second, an external economic shock might cause levels of diversity and

[8] We experiment with a crude proxy by interacting the number of employees in the firm with the relevant industry-level share of graduates, assuming that bigger firms of a given industry type will employ a larger number of skilled workers. F-tests suggests the control makes little difference to overall model performance, so we exclude it from the final specification.
[9] Controls pass Wald and LR tests of joint significance. We also experiment with an index of management ability using principal components analysis. The Index has a strong positive relationship with innovative activity; however, for easier interpretation we prefer to use separate controls.

innovative activity to rise at the same time. The natural experiment conditions reduce the risk of simultaneity and positive selection at *city level*, a common problem in studying the local economic effects of migration and diversity (Borjas 1994).[10]

Two further issues are harder to deal with. Although city-level positive selection is minimised by the choice of years, *individual* migrant and minority owners/partners may still be positively or negatively selected (see section 3). There also is potentially both-ways causation at *firm level*: current innovative activity may affect values of controls and diversity (if more successful firms attract a more diverse workforce). For the first of these we conduct separate robustness tests, using a subset of company founders. In the second case we construct a synthetic cross-section at sector-borough level and use a shift-share instrument to check causality. See section 8 for further details.

6) Results

The main results of the analysis are set out in Tables 4-13. Tables 4-7 inclusive present the findings for the whole sample, focusing on simple measures of migrant and minority ethnic owners/partners. Tables 8-9 give more detailed results on aspects of ownership diversity, focusing on firms with all-migrant teams. Tables 10-13 perform an alternative breakdown into knowledge intensive and non-knowledge intensive firms. In all cases, specification (1) presents results with controls only. Other specifications include DIV and controls.

The model generally performs well.[11] Tests suggest the model is generally well-

[10] If migrants choose to live in cities with the best economic performance, measures of economic success (such as innovation) might be correlated with higher diversity, even though the latter may have no causal effect. By choosing a period where London's diversity was largely set by exogenous policy factors, we minimise this risk. However, we cannot fully eliminate the risk that deeper structural factors may simultaneously influence both diversity and economic performance (such as London's historic position as a large and cosmopolitan milieu).

[11] The numbers of observations differs slightly according in each specification. This is because the clogit command normally drops observations that perfectly predict success or failure. These have coefficients of +/- infinity: dropping them has no effect on estimates of other coefficients, and increases the stability of the estimation process. Some observations are always dropped, so *n* is always less than 7,425. However, the number dropped never exceeds 4.8% of the total sample. In turn, this suggests the model is a generally good fit for the data.

specified, and collinearity is not an issue (mean VIF is about 1).[12] Controls are of the expected sign, magnitude and significance. As expected, collaborative activity, R&D spending and management ability all appear to play important roles in explaining innovative activity. In line with other literature (e.g. Wood 2006), firms in KIBS sectors are more likely to engage in innovation. The square root of firm size is usually significant, suggesting size effects on innovation fall away in large organisations.

6.1 Results for ideas generation

Tables 4 and 5 look at the association between our diversity measures and the introduction of new ideas. In all cases, and as suggested in the secondary literature, ownership diversity in firms has a small but significant link to innovative activity. Table 4 focuses on product innovation. The coefficient of *migown* is 0.161 on new products/services, significant at 1%. This suggests that compared to firms with no migrant owners/partners, the odds of introducing a new product or service are exp(0.161) = 1.75 times higher in firms with at least one non-UK-born owner/partner. The corresponding coefficient of *ethown* is 0.221, significant at 1%, suggesting firms with at least 50% minority ethnic owners/partners are 1.25 times more likely to introduce a new product or service.

Table 5 looks at process innovation. Coefficients of *ethown* are higher than *migown*, with greater significance levels. For instance, the coefficient of *ethown* on *procin*1 is 0.207, significant at 1%: this implies firms with at least 50% minority owners/partners are 1.23 times more likely to have introduced new equipment. The corresponding coefficient for *migown* is 0.146 significant at 5%. For *procin2*, the coefficient of *migown* is 0.137 (5%), while *ethown* is 0.249 (1%). In both cases, firms with some ownership diversity are more likely to introduce new ways of working than less diverse organisations.

6.2 Results for commercialisation

Tables 6 and 7 shift the focus to commercialisation of product and process innovations. Compared to the earlier results, very few of the diversity variables have a significant link to

[12] Output available on request. Models featuring prodin2 and migown_1, procin2 and ethown fail a linktest, but the problem is marginal (the p-value of _hatsq is 0.09). We are not unduly concerned by these results, as the sample size (over 7,000) allows us to assume asymptotics.

the commercialisation of new ideas. For product innovation, none of the coefficients of DIV are significant, and in the case of *migown* are close to zero (Table 6). *Ethown* has some significant links to the successful exploitation of new processes: for *gprocin2* its coefficient is 0.295 (significant at 1%). The latter suggests that firms with at least half minority ethnic owners/partners are 1.34 times more likely to have introduced new ways of working – and raised annual revenue by at least 10%. While the diversity of London firms is strongly linked to new ideas generation, then, it plays less of a role in successfully taking these ideas to market.

6.3 Aspects of diversity

Tables 8 and 9 extend the analysis to look at aspects of diversity in more detail, focusing on firms with entirely migrant owner/partners (as opposed to firms with either some or no owner / partners born outside the UK). LABS only provides this level of information for country of birth, so we are unable to observe ethnic diversity.

Table 8 gives the results for ideas generation. For migrant-only teams, DIV is significant on both measures of process innovation. For new equipment, the coefficient of DIV is 0.167 (10%), and for new ways of working, 0.152 (also 10%). In both cases, these coefficients are larger than for *migown* – so that migrant-run firms have a stronger link to process innovation than diverse teams. For product innovation, by contrast, DIV is significant on *prodin2*, but the cofficient is smaller than for *migown* (0.161 versus 0.167, both at 5%). Table 9 extends the results to commercialisation. As with the previous results, DIV is non-significant on all dependent variables.

6.4 ‘Knowledge intensive’ activity

For some of the process innovation measures, almost all KIBS firms appear to innovate; the coefficient of *kibs* is very high with a large standard error. As a basic cross-check we substitute in the TWF definitions of ‘knowledge-intensive’ sectors.

Because the TWF definition is operationalised at 3-digit SIC level, the same as our sectoral fixed effects, we need to split the sample. Tables 10-13 summarise the results. As with the full sample, cultural diversity has a small but significant association with measures of ideas generation (Tables 10 and 11). Interestingly, the results vary significantly by knowledge-intensity. For knowledge intensive firms, only coefficients of *ethown* are significant (for *prodin1* and *procin1*). By contrast, for less knowledge-intensive businesses, both *migown* and *ethown* are significant in most cases. For these firms, he strongest diversity-innovation links are for process innovation. For instance, for *procin2*, coefficients of *migown* and *ethown* are 0.197 and 0.310 (both 1%), compared with 0.137 and 0.249 for the full sample.

Once again, there are few significant diversity effect associated with the commercialisation of new ideas (Tables 12 and 13). For knowledge intensive firms, surprisingly, no coefficients of DIV turn out to be significant. For non-knowledge intensive firms, as above, the strongest results are for commercialisation of process innovations, particularly for *ethown*.

7. Market orientation

The previous section examined some of the channels through which diversity-innovation effects might operate – configurations of management teams, the role of 'ethnic entrepreneurs' and the importance of knowledge intensive activity. This section extends the analysis to look at firms' market orientation. It is useful to know whether there is any significant difference between the markets served by diverse firms and those served by other firms in the sample. If diverse firms are particularly geared towards very local markets, this implies that London's large and diverse consumer economy is part of the diversity effect. Conversely, if diverse firms are more internationally orientated, the combination of diaspora networks and London's connectivity may be more important.

LABS provides information on market orientation at various levels.[13] We use this to break down a firm's market share into three parts: the share of sales within London (*mktshare_local*), sales within the rest of the UK (*mktshare_national*) and sales to the rest of the world (*mktshare_intl*). Table 15 provides descriptives. We can see that overall, firms in the sample are very much orientated towards markets in London, which account for nearly

[13] Although not all firms answer these questions, so *n* is slightly smaller for these regressions.

three quarters of sales. By contrast, markets outside the UK account for just over six percent of sales. To establish whether firms' cultural diversity has any influence on markets served, we estimate a simple model:

$$Y_{it} = a + bDIV_{it} + \boldsymbol{CONTROLS}_{it}c + SECTOR_i + YEAR_t + e_i \qquad (2)$$

Here, Y is one of our sales share measures, DIV is one of our diversity measures and CONTROLS is a reduced set of controls (firm age, firm size and its square root, dummies for collaboration and R&D spending, plus the four management ability measures, year and SIC3 dummies). We fit the model as seemingly unrelated regressions (using sureg), which provides some efficiency gains from OLS.[14]

Results are given in Tables 16-18. London firms with at least some migrant owners / partners are significantly more orientated towards local and international markets. Table 16 shows that the coefficient of *migown* on local sales is 2.012, significant at 5%; for international sales it is 2.180, significant at 1%. Strikingly, the coeffient of *migown* on national sales is -4.192, significant at 1%. These suggest that compared to firms with all UK-born owners / partners, diverse firms' have London and international shares of sales which are around two percentage points higher. Conversely, firms with at least some migrant owners / partners tend to have smaller sales to the rest of the UK.

Table 17 gives results by ethnic group. Firms with at least half minority ethnic owners or partners tend to be more locally orientated, with lower national and international sales shares. The coefficient of *ethown* on local sales is 6.835, significant at 1%, suggesting that more ethnically diverse firms have nearly 7% higher local sales than more homogenous businesses. For national sales, the coefficient of *ethown* is -5.803, significant at 1%.

For migrant-run firms, the results are similar to the results for *migown*, although coefficients are smaller and the coefficient on local sales is only marginally significant (Table 18). The results suggest that compared to less diverse firms, migrant-run organisations have a 1.465% higher share of international sales.

[14] Output from OLS regressions is available on request.

The results suggest the market orientation of diverse firms in London is markedly different from the average firm in the sample. For these firms, the capital's large and diverse consumer markets are an important source of revenue. This is particularly the case for firms with a majority of minority ethnic managers. For firms with migrant owners and partners, international markets also matter: London's diasporas (and connectivity) are also in play.

8) Robustness checks

Our analysis may be affected by endogeneity problems at individual, firm and city level. As discussed above, city-level positive selection is minimised by our choice of sample years: individual and firm-level challenges remain. We take each in turn.

8.1 Individual selection bias

We need to check how far individual-level processes explain estimates of DIV. Migrant and minority ethnic owners / partners may be highly 'entrepreneurial', and more likely than the average worker to develop new ideas and/or start new firms. Conversely, 'ethnic entrepreneurs' may be forced into starting their own businesses through exclusion from other economic institutions (Gordon et al 2007). Positive selection of entrepreneurial individuals may explain the links between diversity and ideas generation . If this entirely accounts for diversity-innovation effects, coefficients of DIV will be biased upwards. By contrast, negative selection may explain the lack of connection between diversity and measures of commercialisation. If migrant and minority owners/partners face discrimination in marketing new ideas, estimates of DIV are biased downwards.

We partly deal with this by including controls for management ability. However, 'talent' is not fully observed via courses and qualifications. We therefore develop further robustness checks, focusing on reasons for firm formation. LABS allows us to identify respondents directly involved in founding each firm, and their motivation for doing so. We can observe some migrant founders by identifying firms where both the respondent is a founder, and all owners/partners are non-UK born.[15] We identify the share of founders who set up firms for reasons roughly corresponding to 'entrepreneurial' behaviour (e.g. 'I wanted to start my own business'), and for reasons that may reflect exclusion (e.g. 'I found it hard to get work').[16] We then construct dummies for 'entrepreneurial founders', 'locked out founders' and 'other founders', by country of birth.[17]

Table 19 gives descriptives. Around 59% of all respondents were involved in firm formation; migrant founders comprise 14% of the sample, and 23% of all founders. Compared to founders as a whole, a higher share of migrant founders appear to have founded the firm for entrepreneurial reasons, with a lower share locked out. Pearson tests, not reported here, suggest significant correlations between being an entrepreneurial founder and being a migrant; there is also a significant link between lockout and migrant status.

We then run two checks. First, we regress reasons for firm formation on migrant status, management ability and migrant-ability interaction terms. We fit the model as a conditional logit with year and SIC3 dummies. Results are given in Table 20. Being a migrant founder slightly raises the possibility of entrepreneurial firm formation; migrant status has no significant link to other types of start-up. This suggests some role for positive selection, although models are not a great fit.

Second, we test whether an entrepreneurial or locked out migrant founder affects firm-level innovation. To do this, we simply substitute *mig_entrep*, *mig_lockout* and *mig_other* into DIV in equation (1). Table 21 summarises the results. In contrast with the full panel (tables 4-7), there are almost no significant associations between entrepreneurial or

[15] We are unable to observe all migrant founders in this way (e.g. migrant founders of firms with a mixed management team are excluded) We are also unable to identify minority ethnic company founders.

[16] Specifically, we select the three most common 'entrepreneurial' and 'excluded' reasons for firm formation. For the former, these are 'I wanted to start my own business' (q14_2), 'I wanted a new challenge' (q14_5), 'I wanted to be my own boss' (q15_12). For the latter, these are 'I was made redundant' (q14_3), 'I found it hard to get work' (q14_10) and 'My old business collapsed' (q14_23).

[17] This approach is the best use of available data, although it is open to challenge. Our measures of 'attitude' are imperfect and involve some subjective judgement. More seriously, survey answers are likely to exaggerate positive reasons for firm formation, while playing down negative reasons. So the results are likely to overstate positive selection and understate negative selection.

locked-out migrant founders, and innovative activity.

Overall, these results suggest that positive selection of individual migrants plays some role in firm formation. This is a useful finding in itself, as it still suggests that the positive selection of the migrants who come London is economically beneficial. However, this kind of ethnic entrepreneurship is not strong enough to explain our findings. Rather, a combination of individual, firm-level and urban-level diversity-innovation effects seem to be operating in London.

8.2 Firm-level endogeneity issues

Our model in (1) may be affected by reverse and/or both-ways causation. Even if firm-level diversity facilitates innovation, innovative firms may also attract a more diverse workforce, particularly if entrepreneurial individuals are attracted to these firms. In this instance, coefficients of DIV are likely to be biased upwards (although theoretically, simultaneity might involve a downward bias).[18] To assess the extent of this problem we use an instrumental variables approach.

Suitable instruments are not easy to find: as our sample is a repeat cross-section we are unable to use lagged data, and matching firms in LABS with other firm-level microdata would be extremely complex. We examine two main candidates for potential instruments. First, migrants tend to cluster in certain industries (Green 2007) so that migrant-intensive sectoral characteristics might form the basis of an instrumentation strategy. We test a number of shift-share instruments based on historic sectoral characteristics – however, these fail first stage tests (largely because sectoral properties may also influence innovative activity).[19]

Second, migrants and minority ethnic groups tend to cluster in certain urban

[18] This may arise if less innovative firms have fewer opportunities to recruit from the mainstream labour market and recruit individuals – such as those from ethnic minorities or migrant groups – who face discrimination in the wider labour market.

[19] These are: (1) a shift-share instrument based on Ottaviano and Peri (2006) which generates predicted ethnic / migrant shares in particular sectors based on 2003 data and changes in London's population over the period 2003-2007, (2) an interaction term between borough level diversity in 2001 and diversity at the firm or sectoral level, and (3) by collapsing the data to sector / borough averages for 2007 and using the lagged values for sector / borough diversity in 2003.

neighbourhoods: historic location patterns have been used elsewhere in the literature (e.g. Altonji and Card 2001, Ottaviano and Peri 2006). We develop a very simple instrument, which we deploy for the 2007 cross-section. For firms in a given borough, we substitute firm-level DIV with historic borough-level migrant and minority population shares. For firm *i* in borough *j* and year *t*, the instrument takes the form:

$$pDIV_{ijt} = DIV_{jtbase} \tag{3}$$

In this case, *t* is 2007 and *tbase* is 2001, with historic diversity data drawn from the 100% sample provided by the 2001 UK Census. Specifically, to instrument *ethown* we use the proportion of the population of the borough in which the firm is located, who are not of white ethnicity in 2001. To instrument *migown_1ormore* we use the proportion of the borough population who were not born in the UK.

The results from the IV estimation are given in table 22. Following Cameron and Trivedi (2010) we estimate in 2SLS with robust standard errors (using ivreg2). The instruments pass basic first stage tests of validity, with an F-statistic of 13.79 – 63.38, and pass Kleinbergen-Paap tests for under-identified and weak instruments.

The instrument for *ethown* performs far better than the instrument for *migown* or *migown_1ormore.* This may be because *ethown* - which takes the value one if more than half a firms owners are members of ethnic diversity – is a closer measure of 'diversity' than either *migown_1ormore* or *migown* which only cannot account for shares of ownership who are migrants.

Only one relationship survives this test, with a significant and positive effect of *ethown* on *procin2* – whether a firm has introduced new ways of working. While the coefficient on *ethown* is always positive, those for *migown* and *migown_1ormore* are negative (note that the instrument in these cases is considerably weaker).

These results suggest that endogeneity is present at the firm level, but are subject to heavy caveats regarding the validity of the instrument. In particular, we lose a great deal of precision by instrumenting dummies with continuous variables, and are only able to use the instrument on a single cross-section.[20] The cautious conclusion is that simultaneity is likely to be present, and given that this will bias DIV upwards, the main results should be interpreted as upper bounds rather than point estimates.

9) Discussion

This paper has investigated whether culturally diverse firms in London are more innovative, and so whether this cultural diversity is an economic asset to the city, in terms of its impact on innovation. The analysis focuses on the role of migrant and minority business owners / partners, using a survey of 7,400 firms in 2005-7. This period coincided with a major policy-driven increase in net migration to London, providing an ideal opportunity to examine potential diversity-innovation links. As far as we are aware, this is the first research to look at cultural diversity, innovation and cities in UK firms.

We find some evidence to suggest that diverse firms are more innovative. There are small but robust effects of management team diversity on the development and implementation of new products and processes. However, there is little connection between diversity and the successful commercialisation of new ideas.

In contrast to the wider literature, which emphasises the role of diversity for 'knowledge-based' firms, we find diversity-innovation effects across London's industrial structure. Compared to the average firm, diverse firms are more orientated towards London's large and diverse consumer markets – and markets in the rest of the world. The talents and skills of 'ethnic entrepreneurs' (especially migrants) explain part of our findings, but London's diasporic communities, home markets and international connectivity also play important roles.

There are some important caveats to our findings. First, we use relatively noisy

[20] We experiment with various workarounds. Using an alternative continuous measure of diversity, *migown*, the results were very similar. To overcome the lack of a true panel, we also constructed a synthetic panel at sector/borough level, following the approach of Angrist (1991) and Deaton (1985). In practice finding a suitable grouping variable proved difficult, and the final panel was not stable enough to provide reliable results.

measures of 'cultural diversity' that arguably understate the true richness of the capital's people mix. Future research using richer measures of diversity (particularly at individual level) would be welcome. Second, although we are able to control for several endogeneity issues, we are unable to fully deal with potential simultaneity in our results. Simultaneity is likely to bias DIV upwards, so caution suggests that results are interpreted as upper bounds rather than point estimates.

The gap between the ideas generation and commercialisation results needs some examination. One explanation is simply that diverse firms produce new ideas that tend to fail in the marketplace. A more plausible answer is that the measure of commercialisation is too restrictive to capture the benefits of innovation. Many new ideas take time to successfully commercialise, particularly for knowledge-based firms where idea-market-revenue lags may run to several years. Given London's knowledge-focused industrial structure, this may explain some of the gap. In turn, this suggests further research using alternative measures of commercialisation might deliver different results. We experiment with alternative, weaker commercialisation metrics: results are not reported here, but suggest relaxing conditions on revenue growth delivers larger, significant diversity coefficients. Better data on London firms, ideally a true panel, would also help to resolve this question.

A third explanation is that while London's diversity helps firms develop and implement strong ideas, those firms face difficulties bringing their products to market. That suggests co-ordination failures around business support, access to finance and workforce development. These issues are well worthy of future research and the GLA and the London Skills Board could usefully investigate these issues further, through sectoral and/or case study based research.

Overall, the results can be seen as providing support for claims that London's cultural diversity helps support innovative activity, and thus helps strengthen the capital's long-term economic position. In other words, London's diversity is an economic asset, not just a social one.

It is less clear whether they are generalisable to different cities. In theory, we might find similar results for firms in other large UK cities. But London's size, economic structure and demography are unique, and we should be careful in applying these findings. Intuitively, our findings are likely to be replicated in other big British cities – such as Liverpool, Manchester, Glasgow or Birmingham – but diversity-innovation effects may be smaller, or driven by other channels. Further research is needed on a comparative urban scale to establish the wider potential benefits of urban diversity.

Table 1. Correlation matrix of diversity bases, Greater London, 1995-2005.

	% migrants	% ethnic minorities
% migrants	1.0000	
% ethnic minorities	0.9561	1.0000

Source: LFS

Table 2. Summary statistics.

Variable	Description	N	Mean	SD	Min.	Max.
prodin1	Firm introduces new product/service	7425	0.304	0.46	0	1
gprodin1	New product/service, ≥10% revenue growth	7425	0.127	0.333	0	1
prodin2	Firm modifies product/service range	7425	0.257	0.437	0	1
gprodin2	Mod. product/service, ≥10% revenue growth	7425	0.107	0.31	0	1
procin1	Firm introduces new equipment	7425	0.224	0.417	0	1
gprocin1	New equipment, ≥10% revenue growth	7425	0.094	0.291	0	1
procin2	Firm introduces new way of working	7425	0.252	0.434	0	1
gprocin2	New way of working, ≥10% revenue growth	7425	0.105	0.307	0	1
migown	At least 1 non UK-born owner / partner	7425	0.386	0.487	0	1
ethown	At least 50% owners/partners minority ethnic	7425	0.211	0.408	0	1
migfirm	All non UK-born owners / partners	7425	0.219	0.414	0	1
migfirm_d	Base = firms with ≥ migrant owner / partner	2863	0.591	0.492	0	1
lnage	Log age	7425	2.404	1.158	0.693	7.605
lnsize	Log size (employees)	7425	2.133	1.235	0	7.438
collab	Collaborates with other firms	7425	0.29	0.454	0	1
RD	Invests in R&D	7425	0.332	0.471	0	1
export	Exports	7425	0.208	0.406	0	1
plc	PLC status	7425	0.026	0.16	0	1
kibs	KIBS firm	7425	0.192	0.394	0	1
ki	Knowledge-intensive firm	7425	0.475	0.499	0	1
noki	Less knowledge-intensive firm	7425	0.525	0.499	0	1
man_qual	Manager has mgmt qualification	7421	0.468	0.499	0	1
man_course	Manager has completed mgmt course	7398	0.556	0.496	0	1
man_train	Manager has informal / on-job training	7412	0.650	0.477	0	1
man_exp	Manager has previous mgmt experience	7413	0.760	0.426	0	1

Source: LABS

Notes: 1) Not all firms answered questions on management ability, total owners/partners

Table 3. Innovative activity by firm type.

Firm type	prodin1	prodin2	procin1	procin2
All firms	0.304	0.257	0.257	0.257
KIBS	0.306	0.284	0.184	0.249
Knowledge intensive	0.317	0.288	0.228	0.266
Non-knowledge intensive	0.292	0.23	0.221	0.239
	gprodin1	**gprodin2**	**gprocin1**	**gprocin2**
All firms	0.127	0.107	0.094	0.105
KIBS	0.159	0.135	0.090	0.121
Knowledge intensive	0.149	0.132	0.098	0.123
Non-knowledge intensive	0.107	0.085	0.089	0.089

Source: LABS.

Table 4. Firms introducing new or modified products and services, full sample.

Depvar	**prodin1**			**prodin2**		
	(1)	**(3)**	**(7)**	**(1)**	**(3)**	**(7)**
migown_1ormore		0.161***			0.173***	
		(0.057)			(0.062)	
ethown			0.221***			0.124
			(0.075)			(0.079)
lnage	-0.133***	-0.129***	-0.127***	-0.049*	-0.046*	-0.046*
	(0.030)	(0.029)	(0.029)	(0.026)	(0.026)	(0.026)
lnsize	-0.041	-0.035	-0.025	-0.097	-0.091	-0.088
	(0.080)	(0.081)	(0.080)	(0.083)	(0.083)	(0.083)
lnsize_2rt	0.408*	0.393*	0.389*	0.439**	0.422*	0.428*
	(0.210)	(0.211)	(0.207)	(0.219)	(0.220)	(0.218)
collab	0.592***	0.595***	0.601***	0.489***	0.492***	0.493***
	(0.069)	(0.069)	(0.069)	(0.064)	(0.064)	(0.064)
RD	0.929***	0.932***	0.932***	0.731***	0.734***	0.733***
	(0.058)	(0.058)	(0.058)	(0.070)	(0.070)	(0.070)
export	0.077	0.067	0.083	0.020	0.008	0.023
	(0.073)	(0.073)	(0.072)	(0.082)	(0.082)	(0.083)
plc	0.546***	0.531***	0.549***	0.377***	0.361***	0.378***
	(0.164)	(0.165)	(0.165)	(0.108)	(0.105)	(0.108)
man_qual	0.113	0.095	0.088	0.145*	0.124	0.130*
	(0.091)	(0.092)	(0.090)	(0.079)	(0.076)	(0.079)
man_course	0.176***	0.174***	0.175***	0.275***	0.273***	0.274***
	(0.065)	(0.065)	(0.066)	(0.078)	(0.077)	(0.078)
man_train	0.224***	0.224***	0.225***	0.246***	0.245***	0.246***
	(0.084)	(0.084)	(0.084)	(0.079)	(0.079)	(0.079)
man_exp	0.076	0.080	0.092	0.116	0.120*	0.125*
	(0.081)	(0.081)	(0.080)	(0.072)	(0.073)	(0.072)
kibs	0.695***	0.666***	0.714***	0.588***	0.558***	0.600***
	(0.067)	(0.065)	(0.069)	(0.069)	(0.071)	(0.069)
N	7349	7349	7349	7327	7327	7327
Pseudo R2	0.088	0.089	0.090	0.066	0.067	0.066
Log-Likelihood	-3738.689	-3734.951	-3733.697	-3597.901	-3593.785	-3596.411
DF	13	14	14	13	14	14

Source: LABS. Notes: Results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 5. Firms introducing new equipment or ways of working, full sample.

depvar	procin1			procin2		
	(1)	(3)	(7)	(1)	(3)	(7)
migown_1ormore		0.146**			0.137**	
		(0.070)			(0.064)	
ethown			0.207**			0.249***
			(0.087)			(0.076)
lnage	0.008	0.011	0.013	-0.105***	-0.102***	-0.098***
	(0.024)	(0.023)	(0.023)	(0.031)	(0.030)	(0.031)
lnsize	0.009	0.014	0.024	-0.054	-0.050	-0.037
	(0.098)	(0.099)	(0.097)	(0.071)	(0.071)	(0.070)
lnsize_2rt	0.341	0.327	0.321	0.510***	0.498***	0.489***
	(0.232)	(0.233)	(0.230)	(0.170)	(0.171)	(0.170)
collab	0.277***	0.280***	0.284***	0.356***	0.359***	0.365***
	(0.084)	(0.083)	(0.082)	(0.073)	(0.072)	(0.072)
RD	0.565***	0.567***	0.567***	0.639***	0.640***	0.642***
	(0.069)	(0.069)	(0.067)	(0.064)	(0.064)	(0.063)
export	-0.191**	-0.200**	-0.186**	-0.119*	-0.128*	-0.112*
	(0.087)	(0.087)	(0.087)	(0.067)	(0.067)	(0.067)
plc	0.207	0.194	0.210	0.011	-0.002	0.012
	(0.161)	(0.160)	(0.161)	(0.167)	(0.168)	(0.168)
man_qual	0.127**	0.110*	0.103	0.043	0.026	0.012
	(0.064)	(0.063)	(0.064)	(0.062)	(0.064)	(0.067)
man_course	0.229***	0.227***	0.227***	0.286***	0.285***	0.286***
	(0.071)	(0.071)	(0.070)	(0.074)	(0.074)	(0.074)
man_train	0.072	0.072	0.072	0.326***	0.327***	0.328***
	(0.068)	(0.068)	(0.068)	(0.051)	(0.051)	(0.051)
man_exp	0.008	0.011	0.021	0.070	0.073	0.086
	(0.061)	(0.061)	(0.062)	(0.063)	(0.064)	(0.065)
kibs	13.669***	13.284***	13.321***	0.272***	0.245***	0.288***
	(1.005)	(1.000)	(1.006)	(0.067)	(0.067)	(0.069)
N	7298	7298	7298	7303	7303	7303
Pseudo R2	0.038	0.039	0.039	0.057	0.058	0.059
Log-Likelihood	-3472.763	-3469.994	-3468.861	-3668.878	-3666.253	-3662.770
DF	14	15	15	13	14	14

Source: LABS. Notes: Results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 6. Firms commercialising new/modified products/services, full sample.

depvar	gprodin1			gprodin2		
	(1)	(3)	(7)	(1)	(3)	(7)
migown_1ormore		0.088			0.081	
		(0.093)			(0.092)	
ethown			0.155*			0.095
			(0.087)			(0.100)
lnage	-0.442***	-0.439***	-0.437***	-0.415***	-0.412***	-0.412***
	(0.061)	(0.061)	(0.061)	(0.051)	(0.050)	(0.051)
lnsize	-0.004	-0.002	0.005	-0.092	-0.090	-0.087
	(0.084)	(0.084)	(0.086)	(0.121)	(0.121)	(0.122)
lnsize_2rt	0.335	0.328	0.324	0.544*	0.537*	0.538*
	(0.206)	(0.205)	(0.208)	(0.278)	(0.277)	(0.278)
collab	0.605***	0.606***	0.610***	0.539***	0.540***	0.542***
	(0.097)	(0.097)	(0.097)	(0.101)	(0.101)	(0.102)
RD	0.697***	0.698***	0.700***	0.653***	0.654***	0.655***
	(0.078)	(0.078)	(0.077)	(0.097)	(0.097)	(0.097)
export	0.096	0.089	0.100	0.058	0.052	0.061
	(0.086)	(0.084)	(0.086)	(0.108)	(0.109)	(0.107)
plc	0.318*	0.308*	0.317*	0.236	0.228	0.235
	(0.171)	(0.170)	(0.172)	(0.184)	(0.184)	(0.185)
man_qual	0.059	0.047	0.038	0.047	0.036	0.035
	(0.097)	(0.101)	(0.099)	(0.109)	(0.108)	(0.111)
man_course	0.139	0.138	0.139*	0.260***	0.260***	0.260***
	(0.085)	(0.084)	(0.084)	(0.091)	(0.091)	(0.091)
man_train	0.065	0.064	0.064	0.065	0.065	0.065
	(0.118)	(0.118)	(0.118)	(0.122)	(0.122)	(0.122)
man_exp	0.087	0.089	0.099	0.163	0.165	0.170
	(0.105)	(0.105)	(0.104)	(0.114)	(0.114)	(0.114)
kibs	0.251***	0.237***	0.269***	-0.008	-0.020	0.004
	(0.075)	(0.077)	(0.075)	(0.081)	(0.078)	(0.083)
N	7236	7236	7236	7157	7157	7157
Pseudo R2	0.100	0.100	0.101	0.100	0.100	0.100
Log-Likelihood	-2255.294	-2254.675	-2253.999	-1997.740	-1997.289	-1997.320
DF	14	14	15	13	14	14

Source: LABS. Notes: Results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 7. Firms commercialising new equipment/ways of working, full sample.

depvar	gprocin1			gprocin2		
	(1)	(3)	(7)	(1)	(3)	(7)
migown_1ormore		0.140			0.070	
		(0.091)			(0.089)	
ethown			0.163			0.295***
			(0.115)			(0.114)
lnage	-0.310***	-0.306***	-0.305***	-0.424***	-0.422***	-0.415***
	(0.058)	(0.057)	(0.058)	(0.042)	(0.041)	(0.042)
lnsize	-0.037	-0.035	-0.026	-0.019	-0.017	-0.002
	(0.117)	(0.116)	(0.116)	(0.133)	(0.133)	(0.133)
lnsize_2rt	0.529*	0.520*	0.517*	0.535	0.530	0.518
	(0.312)	(0.311)	(0.311)	(0.350)	(0.351)	(0.353)
collab	0.493***	0.496***	0.499***	0.415***	0.416***	0.426***
	(0.125)	(0.123)	(0.124)	(0.084)	(0.083)	(0.084)
RD	0.508***	0.510***	0.510***	0.560***	0.561***	0.565***
	(0.094)	(0.094)	(0.093)	(0.087)	(0.087)	(0.086)
export	-0.143	-0.152	-0.138	0.060	0.055	0.072
	(0.114)	(0.114)	(0.114)	(0.118)	(0.118)	(0.117)
plc	-0.004	-0.016	-0.003	-0.244	-0.251	-0.245
	(0.215)	(0.212)	(0.216)	(0.229)	(0.230)	(0.230)
man_qual	0.050	0.032	0.030	0.121	0.111	0.082
	(0.091)	(0.089)	(0.091)	(0.104)	(0.103)	(0.106)
man_course	0.167	0.167	0.166	0.133	0.133	0.132
	(0.107)	(0.107)	(0.106)	(0.094)	(0.094)	(0.095)
man_train	0.048	0.048	0.047	0.228**	0.228**	0.227**
	(0.107)	(0.108)	(0.107)	(0.101)	(0.101)	(0.100)
man_exp	0.034	0.038	0.045	0.132	0.133	0.152
	(0.111)	(0.111)	(0.111)	(0.099)	(0.100)	(0.101)
kibs	12.603***	12.594***	11.755***	-0.186**	-0.198**	-0.156*
	(0.990)	(0.988)	(0.991)	(0.078)	(0.077)	(0.082)
N	7092	7092	7092	7159	7159	7159
Pseudo R2	0.074	0.075	0.075	0.094	0.094	0.096
Log-Likelihood	-1914.047	-1912.792	-1912.911	-2036.430	-2036.091	-2032.277
DF	14	15	15	13	14	14

Source: LABS. Notes: Results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 8. Ideas generation in migrant-run firms, full sample.

Depvar	prodin1	prodin2	procin1	procin2
	(5) dc_mf	(5) dc_mf	(5) dc_mf	(5) dc_mf
Migfirm	0.102 (0.069)	0.161** (0.081)	0.167* (0.086)	0.152* (0.079)
Controls	Y	Y	Y	Y
N	7349	7327	7298	7303
Pseudo R2	0.089	0.067	0.039	0.058
Log-Likelihood	-3737.613	-3595.329	-3470.125	-3666.542
DF	14	14	15	14

Source: LABS

Notes: results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01.
HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 9. Commercialisation in migrant-run firms, full sample.

Depvar	gprodin1	gprodin2	gprocin1	gprocin2
	(5) dc_mf	(5) dc_mf	(5) dc_mf	(5) dc_mf
Migfirm	0.021 (0.109)	0.077 (0.125)	0.145 (0.129)	0.080 (0.110)
Controls	Y	Y	Y	Y
N	7236	7157	7092	7159
Pseudo R2	0.100	0.100	0.075	0.094
Log-Likelihood	-2255.269	-1997.458	-1913.093	-2036.117
DF	15	14	15	14

Source: LABS

Notes: results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01.
HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 10. Firms introducing new/modified products and services, split sample.

Depvar	prodin1				prodin2			
Split	KI		NOKI		KI		NOKI	
	(1)	(3)	(4)	(6)	(1)	(3)	(4)	(6)
Migown	0.154		0.166**		0.122		0.237***	
	(0.096)		(0.068)		(0.078)		(0.089)	
Ethown		0.343***		0.129		0.054		0.190*
		(0.107)		(0.089)		(0.111)		(0.112)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3490	3490	3859	3859	3470	3470	3857	3857
P R2	0.098	0.100	0.086	0.086	0.063	0.063	0.074	0.073
LL	-1770.351	-1766.695	-1954.182	-1955.298	-1794.076	-1794.987	-1793.914	-1795.835
DF	14	14	14	14	14	14	14	14

Source: LABS

Notes: results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01.
HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 11. Firms introducing new equipment / ways of working, split sample.

Depvar	procin1				procin2			
Split	KI		NOKI		KI		NOKI	
	(1)	(3)	(4)	(6)	(1)	(3)	(4)	(6)
Migown	0.095		0.234***		0.099		0.197***	
	(0.116)		(0.079)		(0.102)		(0.073)	
Ethown		0.241**		0.214*		0.207		0.310***
		(0.115)		(0.120)		(0.137)		(0.085)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3447	3447	3851	3851	3466	3466	3837	3837
P R2	0.026	0.027	0.058	0.057	0.050	0.051	0.069	0.070
LL	-1664.837	-1662.983	-1791.013	-1792.376	-1780.645	-1779.354	-1878.248	-1875.964
DF	14	14	14	14	14	14	14	14

Source: LABS

Notes: results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01.
HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 12. Firms commercialising new/modified products and services, split sample.

Depvar	gprodin1				gprodin2			
Split	KI		NOKI		KI		NOKI	
	(1)	(3)	(4)	(6)	(1)	(3)	(4)	(6)
Migown	0.002 (0.147)		0.180* (0.108)		-0.017 (0.099)		0.210 (0.162)	
Ethown		0.115 (0.118)		0.196 (0.137)		-0.045 (0.133)		0.250 (0.153)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3431	3431	3805	3805	3362	3362	3795	3795
P R2	0.100	0.100	0.107	0.107	0.098	0.098	0.110	0.110
LL	-1187.996	-1187.632	-1059.154	-1059.317	-1086.508	-1086.469	-903.466	-903.420
DF	14	14	14	14	14	14	14	14

Source: LABS

Notes: results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01.
HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 13. Firms commercialising new equipment / ways of working, split sample.

Depvar	gprocin1				gprocin2			
Split	KI		NOKI		KI		NOKI	
	(1)	(3)	(4)	(6)	(1)	(3)	(4)	(6)
Migown	0.024 (0.108)		0.285** (0.136)		0.037 (0.103)		0.128 (0.147)	
Ethown		0.024 (0.152)		0.314* (0.164)		0.166 (0.175)		0.456*** (0.133)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3333	3333	3759	3759	3392	3392	3767	3767
P R2	0.068	0.068	0.092	0.092	0.091	0.092	0.104	0.108
LL	-940.841	-940.847	-961.348	-961.637	-1069.975	-1069.348	-958.943	-954.725
DF	14	14	14	14	14	14	14	14

Source: LABS

Notes: results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01.
HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 14. Local, national and international market shares.

Variable	Obs	Mean	Std. Dev.	Min	Max
mktshare_local	6992	74.68535	33.02737	0	100
mktshare_national	6992	18.92248	27.27774	0	100
mktshare_intl	6992	6.392162	18.83746	0	100

Source: LABS

Table 15. Market orientation and owner/partner diversity: country of birth

% sales	local	national	int'l
migown	1.943*	-4.183***	2.240***
	(1.069)	(0.914)	(0.651)
N	3205	3205	3205
R2	0.284	0.205	0.191
Chi2	26260.750	2587.238	1191.354
p-value	0.000	0.000	0.000
Breusch-Pagan test chi2 statistic			2938.959

Source: LABS. Notes: HAC standard errors in parentheses.
* p<0.1 ** p<0.05 *** p<0.01. All specifications include controls, year and SIC3 dummies.

Table 16. Market orientation and owner/partner diversity: ethnic groups

% sales	local	national	int'l
ethown	6.811***	-5.877***	-0.935
	(1.265)	(1.084)	(0.775)
N	3205	3205	3205
R2	0.290	0.207	0.189
Chi2	26488.352	2602.525	1177.135
p-value	0.000	0.000	0.000
Breusch-Pagan test chi2 statistic			2923.639

Source: LABS. Notes: HAC standard errors in parentheses.
* p<0.1 ** p<0.05 *** p<0.01. All specifications include controls, year and SIC3 dummies.

Table 17. Market orientation and owner/partner diversity: migrant-run firms

% sales	local	national	int'l
migfirm	1.872*	-3.337***	1.465**
	(1.049)	(0.948)	(0.725)
N	3205	3205	3205
R2	0.284	0.202	0.189
Chi2	26248.282	2568.076	1181.131
p-value	0.000	0.000	0.000
Breusch-Pagan test chi2 statistic			2933.440

Source: LABS. Notes: HAC standard errors in parentheses.
* p<0.1 ** p<0.05 *** p<0.01. All specifications include controls, year and SIC3 dummies.

Table 19. Reasons for firm formation, summary statistics.

Cut	N / %
Whole sample	*7425*
% Founders	59.4
% Migrant founders	13.9
Founders	*4409*
% 'Entrepreneurial'	31.9
% 'Locked out'	10.8
% Other	57.3
Migrant founders	*1034*
% 'Entrepreneurial'	35.1
% 'Locked out'	9.6
% Other	55.3

Source: authors' calculations, from LABS.

Table 20. Reasons for firm formation: testing the role of migrant founders.

depvar	entrep (1)	lockout (2)	other (3)
mig_founder	0.324**	0.147	-0.189
	(0.137)	(0.209)	(0.125)
Controls	Y	Y	Y
N	4327	4148	4345
Pseudo R2	0.004	0.008	0.004
Log-Likelihood	-2517.722	-1291.322	-2565.523
DF	11	11	11

Source: LABS. Notes: Results are raw coefficients, not marginal effects. * p<0.1 ** p<0.05 *** p<0.01. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups.

Table 21. Innovation outcomes and firm founders

depvar	prodin1	prodin2	procin1	procin2
mig_entrep	.	.	+	.
mig_lockout	.	.	.	.
mig_other	.	+++	++	+
depvar	**gprodin1**	**gprodin2**	**gprocin1**	**gprocin2**
mig_entrep	.	.	.	.
mig_lockout	.	.	.	.
mig_other	++	.	.	.

Source: LABS.

Notes: " + / - " = positive or negative relationships at standard levels of significance. "." = non-significant relationship.

Table 22. Instrumental variable results.

Depvar	prodin1	prodin2	procin1	procin2
migown_1or~e	-0.25 (0.244)	-0.40 (0.253)	-0.05 (0.211)	-0.25 (0.237)
Controls	Y	Y	Y	Y
N	2663	2663	2663	2663

First stage results	F (1, 2525)	P-value
	13.79	0.000

Source: LABS / 2001 Census.
Notes: * p<0.1 ** p<0.05 *** p<0.01. Robust standard errors in parentheses. All specifications include SIC3 dummies.

Depvar	prodin1	prodin2	procin1	procin2
ethown	0.152 (0.141)	0.0848 (0.133)	0.16 (0.132)	0.528*** (0.146)
controls	Y	Y	Y	Y
N	2663	2663	2663	2663

First stage results	F (1, 2525)	P-value
	63.38	0.000

Source: LABS / 2001 Census.
Notes: * p<0.1 ** p<0.05 *** p<0.01. Robust standard errors in parentheses. All specifications include SIC3 dummies.

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SERC is an independent research centre funded by the Economic and Social Research Council (ESRC), Department for Business Innovation and Skills (BIS), the Department for Communities and Local Government (CLG) and the Welsh Assembly Government.