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Cluster dynamics of financial centres in the United Kingdom: Do connected firms grow faster?

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Abstract

This study investigates the connection between global pipelines and firm growth on a sample of 3,224 financial services firms located in United Kingdom in the aftermath of the global financial crisis. Our findings, based on a spatial econometric model of long-term firm growth, indicate that firms with network connections to related companies in other financial centres grow faster. In contrast, such connections generate substantial negative spatial spillovers to proximate firms, leading to a divergence of growth rates between globally connected and locally embedded firms.

Keywords: firm growth, knowledge spillovers, global pipelines

JEL classifications: F30, F60, F65, G24, R30

Introduction

The aftermath of the global financial crisis (GFC) has seen a sharp reduction in employment in financial services in the United Kingdom[1], shrinking bank balance sheets[2] and reduction in global corporate finance and investment banking revenue[3] (Cassis and Collier, 2010; Wójcik and MacDonald-Korth, 2015; Wójcik et al., 2017). Underneath the veil of this grim picture, however, there was a lot of variation in the effects of the GFC on individual financial centres (FCs) and even more so on individual firms. Marshall (2013) argues that firms in peripheral regions were affected the most, while those in the largest FCs were somewhat shielded. As shown by Parr and Budd (2000), a highly unequal urban hierarchy of FCs exists in the UK with substantial functional differences between different tiers of FCs. While London hosts most of the big banks and offers a wide range of complementary products (Clark, 2002), the remainder of FCs in the UK, with Edinburgh in the lead, offer only a fraction of the capabilities of London (Wójcik et al., Forthcoming). Consequently, different FCs and firms performed very differently in the post-GFC period. The implications of these processes are far reaching and extend beyond the financial sector due to the interconnectedness between financial services and the real economy (Hall, 2013; Coe et al., 2014).

The financial geography literature offers a number of contributions assessing the effect of GFC on financial services in the UK (Marshall, 2013; Wójcik and MacDonald-Korth, 2015), however a substantial gap remains regarding the variation in growth performance of firms. Pandit et al. (2001) offer an exception regarding the latter point, however their study

[1] Wójcik and MacDonald-Korth (2015) show a decline of 8% (88,000 jobs) in UK financial services employment between 2008 and 2012 using ONS-BRES data.

[2] The average and median total assets growth rates of our sampled companies between 2007 and 2015 are both negative.

[3] Findings of Wójcik et al. (2017) indicate that the global investment banking fees in 2015 were 60.52% of their 2007 value.

predates the GFC and they do not consider the role of network connections. A substantial literature on the link between knowledge and firm growth exists in economics (Evans, 1987; Macpherson and Holt, 2007). Complementing this work with the knowledge-based theory of spatial clustering (Maskell and Malmberg, 1991 a, b; Maskell, 2001; Malmberg and Maskell, 2002; Bathelt et al., 2004; Asheim, 2012) has lead us to a research design that puts knowledge transfers and network connections at the forefront of explaining growth performance of financial services firms.

The primary objective of this paper is to study the links between inter-cluster network connections of financial services firms, their long-term growth rate and the associated spillovers to other financial services firms in their proximity. Albeit not directly observed, the access to knowledge relating to business opportunities, client risk profiles and future collaboration prospects facilitated by inter-cluster network connections are understood as examples of valuable knowledge flowing through these networks, all of which are relevant to future growth prospects of firms. We focus on two research questions – (1) Do financial services firms with network connections to related firms in other FCs grow faster? (2) Do financial services firms located within the proximity of well-connected firms benefit from knowledge spillovers?

We use a sample of 3,224 financial services firms sourced from FAME and estimate a series of spatial econometric models of their average annual growth rates in the 2007 – 2015 period. Our key variable of interest – global pipelines – a proxy for inter-cluster connections to other FCs, has been created using data on capital market deals[4] supplied by Dealogic. Our results indicate that firms with higher levels of inter-cluster connections to large financial centres grow faster ceteris paribus, an effect consistent throughout the UK. Such inter-cluster connections, however, lead to a divergence of growth rates between globally-connected and locally embedded firms. This suggests that any learning processes associated with networking of financial services firms benefit primarily the connected firms and valuable knowledge is not widely broadcast to proximate firms. We interpret these connections as a source of competitive advantage for the connected firm, rather than as a universal increase in the knowledge base shared by firms within its cluster. This implies that during a period of decline in financial services, firms lacking inter-cluster connections are at a decisive disadvantage.

The remainder of this paper is organised as follows. The second section reviews relevant literature on the topic and develops six hypotheses. Section three details the research design and section four presents the results. Finally, section five offers a discussion and provides recommendations for future research.

Literature and hypotheses

Literature on geographical clustering of economic activity and the conceptualizations of clusters can be traced at least as far back as the works of Marshall (1920), Hotelling (1929),

[4] Four product categories of deals are covered – equity capital market (ECM), debt capital market (DCM), syndicated loans (LOANS) and mergers and acquisitions (M&As).

Weber (1929) and Hoover (1937). The trinity of original propositions for clustering of firms advocated by Marshall (1920) – labour force pooling, proximity to buyers and suppliers and sharing of knowledge, still bears relevance. The seminal work of Krugman (1991) on increasing returns to scale and the associated positive externalities of clustering led to a rapid increase in research on clusters. Early contributions followed the work of Jacobs (1969), on the benefits of 'urbanisation economies', and Marshall–Arrow–Romer's on 'localization economies' (Marshall, 1920; Arrow, 1962; Romer, 1986). The break of the century has seen a revival of this literature with the work of Porter (1990, 2000), Sassen (2001) and Swann et al. (1998). While Porter (2000) puts clusters at the centre-stage of understanding competition in modern knowledge-based economies, Swann et al. (1998) developed conceptual and methodological framework for studying the link between firm growth and cluster size, allowing for empirical tests of urbanisation and localisation economies. Sassen (2001) proposed increasing specialisation in FABS firms' activities, availability of skilled labour force, ease of access for clients and ability to utilize locally embedded network resources to deliver project beyond the capabilities of individual firms as sources of agglomeration economies and reasons for increasing centralisation of financial and business services (FABS) firms in urban areas. This body of work therefore develops a link between location of FABS firms in clusters and their competitive capabilities, which are enhanced by their interactions with other related firms.

H.1 – Firms in clusters with larger employment in own and closely related industries grow faster.

H.2 – Firms in clusters with larger employment in all other industries grow faster.

Two groups of empirical evidence are relevant to this paper. Studies on financial geography and FABS firms are most pertinent in terms of their industrial focus. However, they seem to lack robust empirical evidence regarding the role of knowledge transfers and spillovers, particularly at the firm level. For that reason, we also need to engage with wider empirical literature on clusters, knowledge spillovers and firm growth.

The subject of firm growth has attracted a lot of research in economics, giving rise to competing theories linking learning, knowledge, and firm growth (Evans, 1987; Freel, 2000; Macpherson and Holt, 2007). Financial and economic geographers have contributed to these debates by studying the effects of clustering on firm growth (Pandit et al., 2001, Fingleton et al., 2004; Beaudry and Swann, 2009), while contributions from finance and business studies corroborate the link between firm performance and network connectivity (Shipilov, 2006; Hochberg et al., 2007, Ljungqvist et al., 2009).

Geographers studying FABS firms (Pandit et al., 2001; Cook et al., 2007; Jacobs et al., 2011; Bathelt et al., 2014; Shearmur and Doloreaux, 2015) have long been interested in the problem of clustering of firms in urban areas. Cook et al. (2007) present a survey-based evidence on factors affecting the location of financial services firms in London. Their findings corroborate the positive effect of MAR spillovers, while factors underlying Jacobs externalities are associated with both centripetal as well as centrifugal forces. Pandit et al. (2001) study the impact of clustering on firm growth in financial services. Their results indicate positive impact of localisation economies on firm growth as well as on entry of new establishments. Co-location with companies from other sectors does not seem to affect firm growth, however it appears to discourage new entrants. The latter point is consistent with the results of Cook et al. (2007) that list overcrowding of London as a powerful centrifugal force. MAR spillovers have been also widely documented in manufacturing industries with Ellison et al. (2007) showing evidence of labour force pooling, input-output linkages as well as knowledge sharing as sources of localisation economies.

Amin and Thrift (1992) highlight the importance of interconnectedness of clusters through their link to the global economy. Taylor (2004) and Bathelt and Li (2014) use specific structures of interconnectivity, based on the networks of offices and parent – subsidiary ownership links of multinational corporations. In tandem with the expanding literature on cluster interconnectedness, the knowledge creation and knowledge spillovers between co-located firms had quickly taken the centre stage in conceptualizing clusters and their impact on innovation, productivity, and regional economic growth (Maskell and Malmberg, 1999, a, b). One of the key impulses for the emergence of this literature was the apparent dissatisfaction with the earlier cost minimisation approaches to conceptualizing clusters and the increasing importance of innovation and product differentiation as a source of competitive advantage (Maskell, 2001; Malmberg and Maskell, 2002). The concepts of knowledge creation and knowledge sharing between firms had quickly become the leading mechanisms for explaining clustering of firms. Geographical proximity is hypothesized to be of relevance to knowledge sharing, especially so for the sharing of tacit knowledge, which requires at least temporary face to face interactions (Gertler, 2003). Bathelt et al. (2004) argue that isolated clusters can deteriorate from excessive embeddedness and lack of connections to external pools of knowledge. They propose a model featuring both short distance – 'local buzz' and long distance – 'global pipelines' modes of knowledge transmission and challenge the established view that tacit knowledge can only be transmitted within clusters. This body of work therefore extends that of Porter (1990, 2000), Swann et al. (1998) and Sassen (2001) by emphasizing the role of inter-cluster network connections and their impact on the competitiveness of clusters and the firms located within them.

H.3 Firms with inter-cluster connections to related firms outside of their own cluster grow faster.

H.4 Firms with inter-cluster connections to larger clusters of related firms grow faster than those with inter-cluster connections to smaller clusters.

Shipilov's (2006) study of Canadian investment banks indicates that both specialist and generalist banks can enhance their performance by creating network connections spanning structural holes. For venture capital firms, Hochberg et al. (2007) find that network centrality is a strong predictor of performance and enhances probability of a successful exit for venture capital portfolio companies. The role of learning and knowledge transfers in networking between financial firms is also emphasized in the work of Ljungqvist et al. (2009) revealing that investment banking syndicates are often built based on the pooling of expertise and network capital and lead to improved chances of syndicate members obtaining management roles in future syndicates. The role of informal networks in knowledge sharing is shown in the work of Pool et al. (2015), who empirically demonstrate substantial similarities in mutual fund portfolios of fund managers living in the same residential areas. Corroborated by the findings of Trippl et al. (2009), this evidence supports the notion that both codified and tacit knowledge can be transferred at all spatial scales through a variety of formal and informal channels.

The knowledge-based theory of spatial clustering is more cautious regarding the direction of the effect of spatial knowledge spillovers on the performance of firms. Bathelt et al. (2004) do not assert that such localized knowledge flows are either instantaneous or equally beneficial to all members of the cluster. Instead they highlight the importance of absorptive capacity and quality of linkages within clusters as the key determinants of localized knowledge spillovers. Allen's (1977) seminal work on technological gatekeepers offers a conceptual framework to shed light on uneven knowledge sharing. Cowan and Jonard (2004) and Morrison et al. (2013) extend this concept to consider the diffusion of knowledge in spatial clusters. Accordingly, firms that have access to valuable external knowledge through investing into costly network connections outside of their cluster can then behave in two distinct ways in relation to other proximate firms – (1) as 'gatekeeps of knowledge' by sharing this knowledge with firms within their cluster or (2) as 'external stars', by minimising the number of connections with local firms and instead focusing on nurturing their links to firms outside of their cluster (Morrison et al., 2008). Allen (1977) suggested that the process of sharing valuable knowledge between firms is highly selective and there is an expectation of reciprocity. Consequently, the degree to which firms are likely to share knowledge within their cluster depends on the availability of suitable partners (Morrison et al., 2008). While the earlier mentioned work of Bathelt et al. (2004), Taylor (2004) and others emphasized the importance of inter-cluster connections and their importance to positioning of individual clusters in global networks and the associated knowledge flows, it is the body of work discussed in this paragraph that sheds light on the mechanism behind the unequal effect of inter-cluster network connections on individual firms in the cluster. This effect has been hypothesized and empirically shown to depend on whether firms directly develop inter-cluster connections or whether they rely on other firms to facilitate their connection to other significant clusters in their industry. In addition, the attitude of the firms forming inter-cluster connections to other firms in their cluster is understood to play a decisive role regarding how well newly acquired knowledge flows throughout the cluster.

> *H.5 – Firms with inter-cluster connections acquire additional tacit knowledge that is not freely available to other firms in their own cluster. Consequently, the increased competitive pressures cause the growth rates of connected firms and other proximate firms to diverge, leading to observable negative spatial spillovers.*

While the results of Evans (1987), Freel (2000) and related studies of firm growth summarised by Macpherson and Holt (2007) support the links between learning, knowledge, and firm growth, it is still not well understood what the effect of knowledge spillovers on firm growth is. The seminal paper of Jaffe et al. (1993) provides evidence of spatially bounded knowledge spillovers by linking the spatial distribution of patent citations to that of the original patents. Audretsch and Feldman (1996) find further evidence in support of knowledge spillovers from R&D spending to third parties and the consequent positive effect on innovation and productivity. While these studies consider knowledge spillovers as a spatial phenomenon, Zucker et al. (1998) identify traceable market links between universities and private biotech companies in California that comprehensively explain the observed knowledge spillovers. Similarly, Appold (1995) shows on a sample of over one thousand metalworking manufacturers in the U.S. that traceable network collaboration between these firms accounts for the observed agglomeration economies.

The literature on interfirm networks and connections between clusters makes an important point related to the varying value of inter-cluster connections. Bathelt et al. (2004) hypothesize that connections to overseas clusters can help firms to enter large overseas markets and allow them to acquire new knowledge, not available locally. Network connections to firms with distinctively different knowledge bases are expected to allow for more substantial knowledge transfers (Lorenzoni and Lipparini, 1999; McEvily and Zaheer, 1999). This reasoning is extended by Lavie (2006) in the context of resource based view of a firm to a model of external resource usage within networks. Arikan (2009) proposes that higher intensity of engaging with external entities should lead to higher knowledge creation capability of clusters. Network dynamism and inter-cluster connections are shown to aid knowledge acquisition, while excessive reliance on social capital in network formation limits learning (Huggins and Johnston, 2010). Lechner and Dowling (2003) document the role of knowledge and marketing networks throughout evolution of firms and their impact on firm growth.

H.6 – Firms with inter-cluster connections to overseas clusters can achieve more significant knowledge exchanges as well as opening access to new markets and therefore grow faster than those with connections to domestic clusters.

Tallman et al. (2004) extend our understanding of knowledge sharing within clusters by developing a framework, which aims to explain variation in knowledge transfers within clusters and consequently variations in firm performance by offering new knowledge typology and by linking absorptive capacity of firms to different types of knowledge. Similarly, Zaheer and Bell (2005) show that the internal capabilities of firms are at the core of their ability to fully utilize their network position to enhance performance. Eisingerich et al. (2010) show that clusters with more open and stronger networks perform better overall. There is however evidence suggesting that these effects may not be distributed evenly across firms in a cluster. The work of Giuliani (2007, 2011) on knowledge networks in clusters, and that of Torre (2008), Morrison (2008) and Lazaric et al. (2008) on the role of gatekeepers of knowledge, are supportive of this view, and complement it with findings suggesting that firms with advanced knowledge bases, and access to valuable pools of knowledge outside of their own cluster, do not generally broadcast this knowledge indiscriminately to the firms in their proximity. Instead, they have been shown to engage in knowledge transfers with other similarly knowledgeable firms that are expected to be able to reciprocate such transfers. Consequently, the knowledge spillovers within clusters are limited (Tappeiner et al., 2008) and generally aimed towards a carefully selected group of firms (Giuliani, 2007, 2011; Morrison, 2012). Too much similarity in knowledge bases of firms tends to discourage knowledge sharing, as it is perceived that too little can be learned from very similar competitors (Broekel and Boschma, 2012).

Research design

The literature on spatial clustering defines clusters by market and non-market connections among co-located firms, which rely on similar inputs, use similar technologies and knowledge, rather than simply being spatial concentrations of firms from the same industry (Porter, 1990; Krugman, 1991). Consequently, standard industrial classifications are not ideal for defining clusters and can lead to serious omissions in sampling. We begin with selecting two industry categories – commercial banking[5] and investment banking and securities dealing[6], which are at the core of FCs and sample companies with total assets data available in at least one year in the period 2007 – 2009 from the FAME database. We restrict ourselves to those with primary trading address in England, Scotland or Wales[7]. This yields 2,868 companies with the required data available. We then search the Dealogic databases[8] for all advisors that have served UK clients. Given that nationalities of advisors are not available in Dealogic databases, we cross-reference the names of advisors from Dealogic with the FAME database to identify those headquartered in the UK. This results in an overlap of 1,184 companies. We combine these two groups, leading to a sample of 3,224 companies. In terms of industrial structure, commercial banks (39%) and investment banks (33%) dominate our sample. Other types of financial firms are also covered, including consulting firms, based on their participation in advisory roles for the four types of services considered here. In terms of geographical location, our sample is heavily weighted towards Inner London (47.5%) and Outer London (9.8%) NUTS2 regions. However, it also represents the rest of the UK, with 42.7% of sampled companies located outside of the capital city (figure 1).

[5] NAICS 2012 - 522110
[6] 523110
[7] Due to the limitations of our regional employment data sourced from the ONS.
[8] We used data from the Dealogic Equity Capital Market (ECM), Debt Capital Market (DCM), Syndicated Loans (LOANS) and Mergers and Acquisitions (M&As) databases.

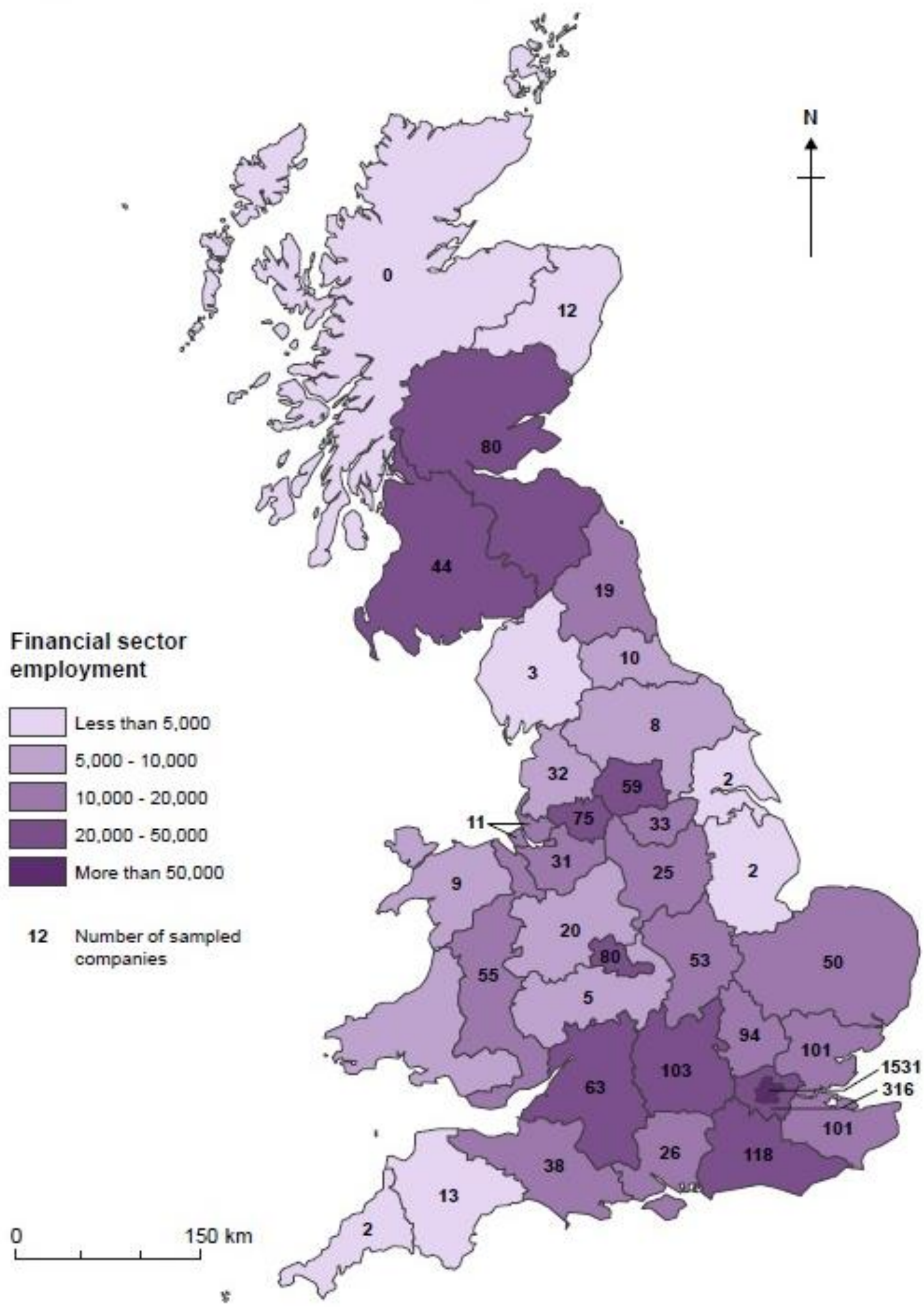

Figure 1 – Spatial distribution of the Sampled Financial Services Firms

Notes: Financial sector employment is the sum of full time employment in financial services activities except insurance and pension funding (SIC 2007 two-digit code 64) plus employment in activities auxiliary to financial services and insurance activities (SIC 2007 two-digit code 66). Employment data has been sourced from the Office for National Statistics (BRES database) and is measured as of 2007. Number of sampled companies is pooled across 2007–2009 and is based on availability of company total assets data from the FAME database. Regional boundaries are defined according to the NUTS 2 2010 classification.

Source: Authors' calculation based on FAME and ONS-BRES data.

We use two related spatial econometric models with local spillovers, presented in the equations below, where (1) refers to the spatial lag of X model (SLX) and (2) is the spatial Durbin error model (SDEM) (Anselin, 2013; LeSage, 2014):

$$y = X\beta_1 + WX\beta_2 + \varepsilon \quad (1)$$

$$y = X\beta_1 + WX\beta_2 + u \quad (2)$$

$$u = \lambda Wu + \varepsilon$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I_N)$$

where y is the dependent variable, X is a vector of explanatory variables, β_1 is a vector of direct effects, W is a spatial weighting matrix, β_2 is a vector of indirect effects, ε is normally distributed residual with mean zero and constant variance, u is a spatially correlated residual and λ is the spatial autocorrelation error coefficient. The β_1 coefficients can be interpreted as partial effects in the same way as in non-spatial models, while the β_2 coefficients are interpreted as the cross-partial derivatives, meaning that they are the average spatial spillovers falling on each first order neighbour[9]. This interpretation of β_2 coefficients relies on the use of binary symmetric adjacency matrix in the place of W. As an alternative and more general specification we have also considered the Spatial Durbin Model (SDM), which includes a spatial lag of the dependent variable in addition to the functional form of the SLX model, however our data does not support the hypothesis that the spatial autoregressive coefficient in this model would be statistically significantly different from zero, which lead us to the specifications outlined above (Vega and Elhorst, 2015).

While spatial econometric models of long term growth are fairly common in studies of regions or countries, they are less common in micro-economic studies (Bell and Bockstael, 2000). Such applications present their unique set of challenges, given that the spatial weight matrix (W) can no longer be meaningfully based on contiguity and positions of agents are not fixed firmly in space. We consider several specifications of W based on varying great circle distances in the range 20-80km to show that our results are reasonably robust to the size of neighbourhood selected (LeSage and Pace, 2014). Our specification of W does not allow for firms to move their head office among cities, however it is robust to relocations within metropolitan areas set by the great circle boundaries specified above. Given that FABS firms seldom move their headquarters from one city to another, we assume that this only has a marginal effect on our results.

[9] Our results present varying specifications of the spatial weighting matrix (W) based on great circle distances between 20-80km. First order neighbours are any companies within the selected great circle distance.

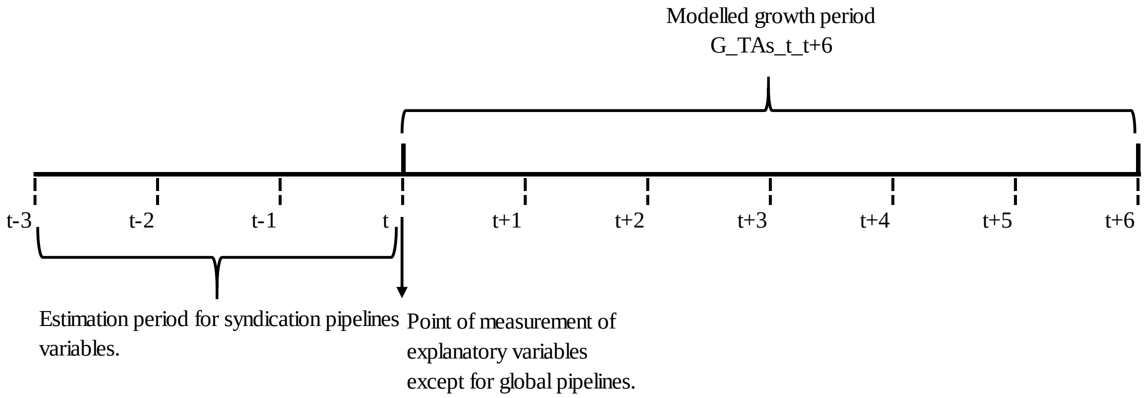

Figure 2 – Relative timing of measurement of variables

Source: Derived from Evans (1987) and Hochberg et al. (2007)

Figure 2 provides a high-level illustration of the setup that we use for our econometric models. Our explanatory variables are measured at the beginning or prior to the growth period modelled[10]. The growth period represents a six-year window, over which we calculate an average annual growth rate of total assets. We also use an eight-year growth period for some of our models, which is constructed following the design illustrated in figure 2. The averaging of growth rates across multiple annual time periods is warranted, given that one year firm growth rates are generally too volatile to model[11]. We therefore define our dependent variables as follows:

$$G_{t1,t2} = \frac{\ln(TA_{t2}) - \ln(TA_{t1})}{\mathrm{t2} - \mathrm{t1}}$$

where $G_{t1,t2}$ is the growth rate of total assets averaged across a (t2-t1) period, $\ln(TA_t)$ - the natural logarithm of total assets at the beginning of the period, and $\ln(TA_{t2})$ - the natural logarithm of total assets at the end of the period.

The set of explanatory variables used in our models is detailed in appendix 1 and the descriptive statistics are in appendix 2. In order to control for clustering of both related and unrelated activities, we construct two variables – natural logarithm of full-time employment in own sector (LN.FT.Emp.Own) and full-time employment in all other sectors (LN.FT.Emp.Other) at NUTS2 level. Own sector in this context is defined as employment in financial services activities except insurance and pension funding[12] plus employment in activities auxiliary to financial services and insurance activities[13]. Employment data has been sourced from the Office for National Statistics – BRES database. Given the potentially important impact of deleveraging in the financial sector during our sample period on the firm

[10] Ownership pipelines data is only available on contemporary basis and we therefore use the records of parent – subsidiary relationships available as of September, 2016.
[11] This is a well-established practice in studies of firm growth (Evans, 1987; Macpherson and Holt, 2007).

[12] SIC 2007 two-digit code 64
[13] SIC 2007 two-digit code 66

growth rates, we also control for leverage by including a ratio of total liabilities to total assets. In studies of firm growth, there is typically a sizeable fraction of the sampled companies for which growth rates are not available, because they have exited the sample during the studied period. If exits are not random and are correlated with explanatory variables in the growth equation, this may result in biased coefficient estimates. To address this problem, we use the Heckman's (1979) correction method for dealing with selection bias in the sampling process.

` Table 1. Classification of global pipelines proxy variables.

Weights \ Type of link	Syndication (all roles)	Syndication (key roles only)	Ownership
Equal	Syndication.Pipelines.AR.Count	Syndication.Pipelines.KR.Count	Ownership.Pipelines.Count
Value weighted by aggregate city fees	Syndication.Pipelines.AR.Value.W	Syndication.Pipelines.KR.Value.W	Ownership.Pipelines.Value.W

Source: Derived from Bathelt et al. (2004), Taylor (2004), Hochberg et al. (2007) and Ljungqvist et al. (2009).

Literature on inter-city connectivity recognises that FABS firms' networks among cities are simply aggregations of links formed by firms. While Taylor (2004) maps the networks of offices of multinational APS firms, others have focused on syndication links among firms as the proxy for network structure (Hochberg et al., 2007; Ljungqvist et al., 2009). To explain the definitions of our proxy variables for global pipelines, we refer to table 1 and equations (3) – (6) in appendix 3. The variables constructed vary along two dimensions – (1) type of link (columns of table 1) and weighting scheme (rows). Companies are considered connected through a syndication link, if they have been the service providers in the same deal, as recorded in the Dealogic databases during the three years preceding the beginning of the studied period. We further distinguish between key roles and lower order roles in syndicates. One specification of this variable is based on including companies regardless of their role (all roles), and another, where we only include those in the lead management roles[14] (key roles). As an alternative to syndication links we consider ownership links, defined as a link between a parent company and its subsidiary in a different city. We either use equal weights, or weight the respective links to financial centres by their size, measured by fees earned from core investment and corporate banking activities[15]. These have been obtained by estimating the fees earned by the top 500 advisors for each product-year combination and allocating them to the city of subsidiary headquarters for each advisor. Data from Dealogic databases have been used to construct these city level aggregates along with a hand collected dataset of addresses of 7,458 advisor subsidiaries.

[14] ECM – bookrunner, DCM – bookrunner, LOANS – bookrunner / mandated lead arranger, M&As – acquirer / target advisor.

[15] We include transactions on primary issues of equity securities, debt securities, syndicated loans and M&As sourced from Dealogic.

The dataset we obtained from FAME had a small number of missing observations on date of incorporation[16] and postcodes[17]. To preserve the sample size, we hand-collected the missing data from a variety of sources including corporate websites, Bloomberg and the Nexis UK. The leverage variable had 60-70% of values missing. Due to the importance of this variable and the large fraction of the sample that would need to be discarded, we estimate the missing values for leverage using the predictive mean matching (PMM) method (Little, 1988), available in the 'mice' R package (Buuren and Groothuis-Oudshoorn, 2011), on the full set of explanatory variables from our main model (table 2). As a robustness check, we rerun our analysis on a dataset of complete observations and compare the results to those obtained from a dataset with 25 imputations of the missing data (table 5).

Results

H.1 - We test the connection between localisation economies and firm growth by examining the coefficient estimates on the LN.FT.Emp.Own variable. The point estimates in table 2 indicate that a 10% increase in the own sector employment would lead to a 0.40% to 0.51% increase in the average annual firm growth rate. This effect can be observed regardless of the definition of global pipelines used (tables 5 and 6) and is robust to the great circle distance used to construct W matrix (table 6). However, the coefficient estimates become imprecise in three out of four models, if we only use complete observations rather than multiply imputed datasets. This highlights the value of treating missing data rather than discarding it.

H.2 - We control for employment in all sectors other than financial services and activities auxiliary to financial services by the LN.FT.Emp.Other variable. The coefficient estimates that we obtain across a range of different functional forms of models, estimators, time periods and samples are overwhelmingly negative, however they are not estimated precisely enough to distinguish them from zero. We can therefore not confirm the existence of a reliable link between urbanisation economies and firm growth.

H.3 - There are six different specifications of global pipelines that we use to model the direct effects of inter-cluster network connections on firm growth (table 4). The value-weighted syndication pipelines, based on syndicated deals featuring advisers in all roles (Syndication.Pipelines.AR.Value.W), is the best performing proxy, as measured by the t-statistics of coefficient estimates. However, this relationship can also be identified using the equally-weighted version of the variable Syndication.Pipelines.AR.Count and the value-weighted syndication pipelines variable based on key roles only (Syndication.Pipelines.KR.Value.W). Neither of the two ownership pipelines variables is statistically significant. A word of caution is needed here. In the research design section, we explained the measurement caveats associated with the ownership pipelines variable. It is possible that future research using similar conceptual specifications, but with different data, will lead to different results.

[16] We used incorporation dates to determine firm age.

[17] We used postcodes to locate firms in space by obtaining the GPS coordinates of the firm's postcode centroid.

The point estimates presented in table 2 indicate a 2.38% to 3.04% increase in average annual growth rate as a result of one standard deviation increase in the value of Syndication.Pipelines.AR.Value.W. Estimating the effect of Syndication.Pipelines.AR.Value.W variable on a reduced sample of complete observations[18] (table 5) corroborates this result. It is however noteworthy that using this sample we get smaller coefficient estimates and the estimated partial effects vary between 1.21% and 2.06%.

H.4 - We uncover a relationship between global pipelines proxy variables and firm growth across multiple specifications of these variables. We now compare the t-statistics of global pipelines proxy variables based on syndication featuring equally-weighted and value-weighted links. We do this primarily to find out, whether the size of FCs to which firms connect via global pipelines matters. A priori we would expect that if one of the weighting schemes was superior to the other, it should lead to more precise coefficient estimates. The t-statistic of coefficient estimate on the Syndication.Pipelines.AR.Value.W variable is 4.85, with a statistical significance at 1% level. In contrast the t-statistic for the coefficient estimate on the Syndication.Pipelines.AR.Count variable is 1.99, significant at 5% level. Given that the t-statistic on the value-weighted syndication pipelines variable is over 2.4 times larger than that on the equally-weighted syndication pipelines variable, this indicates that the size of the clusters to which a firm is connected is highly relevant to modelling firm growth. The result is even more pronounced if we use the 'key roles' specification of the syndication pipelines variable. In this case the t-statistic on the value-weighted variable is 4.33, while that on the equally-weighted variable is 1.34. Consequently, depending on the research design employed, it may be necessary to account for the relative importance of inter-cluster connections to be able to uncover such relationship.

H.5 - To test this hypothesis, we shift our attention to the indirect effects of the global pipelines. The point estimates presented in table 2 suggest that there is a -0.32% to -0.61% decrease in the average annual growth rate of each firm within the proximity of a connected firm for one standard deviation increase in its value-weighted syndication pipelines. It is important to keep in mind that this is not the cumulative effect across all neighbours as customarily presented in studies using row-standardised W, but the average effect on each neighbouring firm. Therefore, particularly in big financial centres with many well-connected firms and even more small and less connected firms, such as London, the resulting competitive pressures could become a substantial impediment to the growth of lesser connected firms. This might explain the relatively higher exit rates of small and young financial services firms evident from our probit estimates presented in table 2. We also estimate these indirect effects of global pipelines at a variety of spatial scales ranging from 20km to 80km in radius. The results are consistent across a wide range of reasonable definitions of a metropolitan area (table 6).

H.6 - The knowledge-based theory of spatial clustering suggests that there is scope for more substantial knowledge transfers, if connections are made with geographically distant firms. To test this proposition, we split our proxy for global pipelines into two variables, one measuring connections to domestic clusters and the other measuring connections to cross-border clusters. Results presented in table 3 provide a mixed evidence.

[18] This is a subset of observations without any missing data or imputations of it.

While for the periods 2007 – 2013 and 2007 – 2015 they indicate that most of the value of inter-cluster connections can be captured by only considering cross-border connections, the results for 2008 – 2014 suggest no statistically significant difference between these estimates, while those for 2009 – 2015 favour domestic connections. It is difficult to say conclusively what may be causing this shift, however it may be symptomatic of the process of progressive de-globalisation of the financial services in the aftermath of the GFC. This proposition certainly warrants further inquiry beyond the scope of this paper.

Finally, given the position of London as a global financial centre and the substantial proportion of our sampled firms based there (57.3%), the question is whether the results presented here regarding knowledge transfers and spillovers are not simply driven by firms sampled from this one city. To address this concern, we interact the Syndication.Pipelines.AR.Value.W variable with a binary indicator variable for primary trading location within London. This allows us to estimate two separate slope coefficients for Syndication.Pipelines.AR.Value.W and determine whether the effect of this variable varies between London and the rest of the UK. As shown in table 7, this relationship in the data is not limited to London and is in fact not significantly different when we compare London with the rest of the UK. This reassures us that the high percentage of London based firms in our sample is not driving our results.

Table 2 - Main results by time period

Main equations	2009 - 2015						2008 - 2014						2007 - 2013						2007 - 2015					
	SLX			SDEM			SLX			SDEM			SLX			SDEM			SLX			SDEM		
	β	***	t-stat	β	***	t-stat	β	***	**t-stat**	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	**t-stat**	β	***	t-stat
Lambda				-0.0030		-1.2403				-0.0110	***	-3.5081				-0.0093	***	-2.8194				-0.0037		-1.3276
Direct effects																								
LN.Age	0.4786	***	(3.7971)	0.4783	***	(3.8353)	0.2834	***	(3.0725)	0.2886	***	(3.1844)	0.1622	*	(1.8994)	0.1604	*	(1.9135)	0.2546	***	(2.9271)	0.2548	***	(2.9650)
LN.Age.2	-0.0646	***	-(3.2563)	-0.0648	***	-(3.3009)	-0.0382	***	-(2.6228)	-0.0400	***	-(2.7907)	-0.0186	.	-(1.5677)	-0.0192	.	-(1.6425)	-0.0302	**	-(2.2059)	-0.0305	**	-(2.2519)
LN.Total.Assets	-0.0453	***	-(4.9786)	-0.0454	***	-(5.0463)	-0.0524	***	-(6.1647)	-0.0534	***	-(6.3943)	-0.0497	***	-(5.8044)	-0.0503	***	-(5.9646)	-0.0420	***	-(6.1363)	-0.0422	***	-(6.2443)
LN.Total.Assets.2	0.0008	*	(1.8294)	0.0008	*	(1.8259)	0.0010	**	(2.3591)	0.0010	**	(2.3572)	0.0013	***	(3.1894)	0.0012	***	(3.1553)	0.0009	***	(2.7056)	0.0009	***	(2.7458)
LN.Age * LN.Total.Assets	0.0010		(0.3288)	0.0011		(0.3739)	0.0014		(0.5195)	0.0019		(0.7448)	0.0000		-(0.0097)	0.0005		(0.1958)	-0.0009		-(0.4090)	-0.0008		-(0.3611)
Syndication.Pipelines.AR.Value.W	0.0262	***	(3.9592)	0.0266	***	(4.0602)	0.0294	***	(4.7441)	0.0299	***	(4.9310)	0.0235	***	(3.8821)	0.0235	***	(3.9491)	0.0252	***	(4.8483)	0.0253	***	(4.9360)
Survival.Prob	-0.1685	*	-(1.8361)	-0.1671	*	-(1.8404)	-0.1121		-(1.2750)	-0.1123		-(1.3019)	-0.1406		-(1.0374)	-0.1365		-(1.0263)	-0.1819	*	-(1.8967)	-0.1804	*	-(1.9049)
LN.FT.Emp.Own	0.0499	**	(2.1073)	0.0530	**	(2.2566)	0.0340	.	(1.5523)	0.0417	*	(1.8389)	0.0481	**	(2.1298)	0.0506	**	(2.1965)	0.0425	**	(2.0538)	0.0439	**	(2.1285)
LN.FT.Emp.Other	-0.0505		-(0.9083)	-0.0522		-(0.9491)	-0.0433		-(0.8062)	-0.0539		-(1.0086)	-0.0492		-(0.9676)	-0.0562		-(1.1146)	-0.0602		-(1.2369)	-0.0622		-(1.2918)
Leverage.TLs.To.TAs	0.0021		(0.8795)	0.0021		(0.8780)	0.0008		(0.1717)	0.0008		(0.1628)	0.0005		(0.3167)	0.0005		(0.3369)	0.0005		(0.4685)	0.0005		(0.4785)
Indirect effects																								
W.LN.Age	0.0483		(1.3807)	0.0460		(1.3467)	-0.0026		-(0.0956)	-0.0019		-(0.0757)	0.0059		(0.2405)	0.0028		(0.1180)	-0.0114		-(0.4029)	-0.0124		-(0.4459)
W.LN.Age.2	-0.0084	.	-(1.5677)	-0.0083	.	-(1.5800)	0.0016		(0.3972)	0.0008		(0.2037)	0.0003		(0.0904)	0.0001		(0.0266)	0.0014		(0.3050)	0.0013		(0.2971)
W.LN.Total.Assets	0.0014		(0.5829)	0.0014		(0.5695)	0.0024		(1.1540)	0.0019		(0.9048)	0.0020		(1.0684)	0.0014		(0.7910)	0.0010		(0.6352)	0.0007		(0.4584)
W.LN.Total.Assets.2	-0.0001		-(1.0883)	-0.0001		-(1.2932)	-0.0001		-(0.6786)	-0.0001		-(1.2026)	0.0000		(0.1628)	0.0000		-(0.1415)	-0.0001		-(0.7217)	-0.0001		-(0.7163)
W.LN.Age * LN.Total.Assets	0.0008		(0.9240)	0.0009		(1.0621)	-0.0001		-(0.1800)	0.0003		(0.4789)	-0.0005		-(0.6283)	0.0000		(0.0055)	0.0005		(0.8079)	0.0006		(0.9988)
W.Syndication.Pipelines.AR.Value.W	-0.0061	***	-(3.2486)	-0.0057	***	-(3.1016)	-0.0043	***	-(2.6909)	-0.0033	**	-(2.2774)	-0.0045	***	-(2.6984)	-0.0043	***	-(2.7527)	-0.0032	**	-(2.0635)	-0.0032	**	-(2.1239)
W.Survival.Prob	-0.0397	*	-(1.7755)	-0.0362	*	-(1.6726)	-0.0182		-(0.7895)	-0.0149		-(0.6862)	-0.0178		-(0.4663)	-0.0115		-(0.3077)	-0.0043		-(0.1582)	-0.0012		-(0.0456)
W.LN.FT.Emp.Own	-0.0029	*	-(1.8778)	-0.0031	**	-(2.0227)	0.0006		(0.3878)	0.0000		-(0.0310)	-0.0005		-(0.3243)	-0.0006		-(0.3997)	-0.0010		-(0.5873)	-0.0010		-(0.6130)
W.LN.FT.Emp.Other	0.0049	.	(1.4990)	0.0051	.	(1.6230)	-0.0041		-(1.2781)	-0.0022		-(0.7333)	-0.0018		-(0.5052)	-0.0015		-(0.4129)	-0.0004		-(0.1187)	-0.0003		-(0.0870)
W.Leverage.TLs.To.TAs	0.0000		(0.0662)	0.0000		(0.0628)	0.0000		(0.0198)	0.0000		-(0.0090)	0.0000		(0.0696)	0.0001		(0.2576)	0.0001		(0.2294)	0.0001		(0.2327)
Adjusted pooled R-squared	0.16						0.18						0.14						0.19					
Survivors	1351						1438						1486						1246					
Sample size (N)	2485						2663						2830						2830					
Survival equations	SLX / SDEM						SLX / SDEM						SLX / SDEM						SLX / SDEM					
LN.Total.Assets	0.3096	***	(8.7330)				0.2356	***	(6.3820)				0.1419	***	(7.8570)				0.1947	***	(9.3330)			
LN.Age	3.6123	***	(19.3820)				2.9341	***	(14.2760)				1.5749	***	(13.7160)				2.6745	***	(19.6900)			
LN.Total.Assets * LN.Age	-0.1484	***	-(7.9590)				-0.0989	***	-(3.6000)				-0.0319	*	-(1.8930)				-0.1066	***	-(7.7330)			

Notes: *** significant at 1% level, ** 5% level, * 10% level; SLX - spatially lagged X model, SDEM - spatial Durbin error model, Lambda - spatial autocorrelation error coefficient; Survival equations are estimated by probit; Note that survival equations are estimated on the full sample (N) and growth (main) equations are estimated on the sample of survivors.

Table 3 - Cross-border vs domestic pipelines

	2009 - 2015						2008 - 2014						2007 - 2013						2007 - 2015					
	[1]			[2]			[3]			[4]			[5]			[6]			[7]			[8]		
	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat
Direct effects																								
LN.Age	0.4786	***	(3.7971)	0.4558	***	(3.6039)	0.2834	***	(3.0725)	0.2798	***	(3.0323)	0.1622	**	(1.8994)	0.1619	*	(1.8922)	0.2546	***	(2.9271)	0.2561	***	(2.9390)
LN.Age.2	-0.0646	***	-(3.2563)	-0.0608	***	-(3.0514)	-0.0382	***	-(2.6228)	-0.0373	**	-(2.5637)	-0.0186	.	-(1.5677)	-0.0186	.	-(1.5603)	-0.0302	**	-(2.2059)	-0.0304	**	-(2.2156)
LN.Total.Assets	-0.0453	***	-(4.9786)	-0.0455	***	-(4.9949)	-0.0524	***	-(6.1647)	-0.0528	***	-(6.2045)	-0.0497	***	-(5.8044)	-0.0497	***	-(5.7817)	-0.0420	***	-(6.1363)	-0.0420	***	-(6.1325)
LN.Total.Assets.2	0.0008	*	(1.8294)	0.0009	**	(2.0656)	0.0010	**	(2.3591)	0.0010	**	(2.4299)	0.0013	***	(3.1894)	0.0013	***	(3.1817)	0.0009	***	(2.7056)	0.0009	***	(2.6920)
LN.Age * LN.Total.Assets	0.0010		(0.3288)	0.0005		(0.1589)	0.0014		(0.5195)	0.0013		(0.4853)	0.0000		-(0.0097)	0.0000		-(0.0124)	-0.0009		-(0.4090)	-0.0009		-(0.3984)
Syndication.Pipelines.AR.Value.W	0.0262	***	(3.9592)				0.0294	***	(4.7441)				0.0235	***	(3.8821)				0.0252	***	(4.8483)			
Syndication.Dom.Pipelines.AR.Value.W				0.0184	**	(2.1348)				0.0164	**	(2.0067)				0.0043		(0.5248)				0.0019		(0.2618)
Syndication.CB.Pipelines.AR.Value.W				0.0121		(1.3834)				0.0167	**	(2.0622)				0.0201	**	(2.4077)				0.0236	***	(3.2666)
Survival.Prob	-0.1685	*	-(1.8361)	-0.1552	*	-(1.6880)	-0.1121		-(1.2750)	-0.1118		-(1.2711)	-0.1406		-(1.0374)	-0.1402		-(1.0332)	-0.1819	*	-(1.8967)	-0.1841	*	-(1.9182)
LN.FT.Emp.Own	0.0499	**	(2.1073)	0.0559	**	(2.3324)	0.0340	.	(1.5523)	0.0334	.	(1.5249)	0.0481	**	(2.1298)	0.0478	**	(2.1143)	0.0425	**	(2.0538)	0.0434	**	(2.0908)
LN.FT.Emp.Other	-0.0505		-(0.9083)	-0.0634		-(1.1303)	-0.0433		-(0.8062)	-0.0442		-(0.8214)	-0.0492		-(0.9676)	-0.0482		-(0.9439)	-0.0602		-(1.2369)	-0.0643		-(1.3136)
Leverage.TLs.To.TAs	0.0021		(0.8795)	0.0021		(0.8804)	0.0008		(0.1717)	0.0008		(0.1744)	0.0005		(0.3167)	0.0005		(0.3146)	0.0005		(0.4685)	0.0005		(0.4763)
Indirect effects																								
W.LN.Age	0.0483		(1.3807)	0.0353		(0.9941)	-0.0026		-(0.0956)	-0.0046		-(0.1707)	0.0059		(0.2405)	0.0058		(0.2383)	-0.0114		-(0.4029)	-0.0123		-(0.4324)
W.LN.Age.2	-0.0084	.	-(1.5677)	-0.0061		-(1.1016)	0.0016		(0.3972)	0.0020		(0.4733)	0.0003		(0.0904)	0.0003		(0.0996)	0.0014		(0.3050)	0.0014		(0.3253)
W.LN.Total.Assets	0.0014		(0.5829)	0.0010		(0.3859)	0.0024		(1.1540)	0.0026		(1.2155)	0.0020		(1.0684)	0.0019		(1.0356)	0.0010		(0.6352)	0.0013		(0.7532)
W.LN.Total.Assets.2	-0.0001		-(1.0883)	0.0000		-(0.0947)	-0.0001		-(0.6786)	-0.0001		-(0.7759)	0.0000		(0.1628)	0.0000		(0.2155)	-0.0001		-(0.7217)	-0.0001		-(0.9051)
W.LN.Age * LN.Total.Assets	0.0008		(0.9240)	0.0004		(0.4525)	-0.0001		-(0.1800)	-0.0001		-(0.1505)	-0.0005		-(0.6283)	-0.0005		-(0.6500)	0.0005		(0.8079)	0.0006		(0.8954)
W.Syndication.Pipelines.AR.Value.W	-0.0061	***	-(3.2486)				-0.0043	***	-(2.6909)				-0.0045	***	-(2.6984)				-0.0032	**	-(2.0635)			
W.Syndication.Dom.Pipelines.AR.Value.W				0.0041		(1.2539)				-0.0017		-(0.6091)				0.0000		-(0.0139)				-0.0029		-(0.9462)
W.Syndication.CB.Pipelines.AR.Value.W				-0.0093	***	-(3.1388)				-0.0030		-(1.1863)				-0.0045	.	-(1.4597)				-0.0009		-(0.2970)
W.Survival.Prob	-0.0397	*	-(1.7755)	-0.0303		-(1.3209)	-0.0182		-(0.7895)	-0.0171		-(0.7395)	-0.0178		-(0.4663)	-0.0177		-(0.4651)	-0.0043		-(0.1582)	-0.0038		-(0.1399)
W.LN.FT.Emp.Own	-0.0029	*	-(1.8778)	-0.0037	**	-(2.2582)	0.0006		(0.3878)	0.0007		(0.4231)	-0.0005		-(0.3243)	-0.0006		-(0.3646)	-0.0010		-(0.5873)	-0.0008		-(0.4792)
W.LN.FT.Emp.Other	0.0049	.	(1.4990)	0.0060	*	(1.8158)	-0.0041		-(1.2781)	-0.0043		-(1.2580)	-0.0018		-(0.5052)	-0.0017		-(0.4562)	-0.0004		-(0.1187)	-0.0008		-(0.2041)
W.Leverage.TLs.To.TAs	0.0000		(0.0662)	0.0001		(0.0834)	0.0000		(0.0198)	0.0000		(0.0281)	0.0000		(0.0696)	0.0000		(0.0694)	0.0001		(0.2294)	0.0001		(0.2640)
corr (Dom.Pipelines, CB.Pipelines)				0.71						0.70						0.72						0.73		
Adjusted pooled R-squared	0.16			0.16			0.18			0.18			0.14			0.14			0.19			0.19		

Notes: *** significant at 1% level, ** 5% level, * 10% level; corr(Dom.Pipelines, CB.Pipelines) is a correlation for the domestic and cross-border syndication pipelines variables.

Table 4 - Global pipelines definitions

	[1]			[2]			[3]			[4]			[5]			[6]		
	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat
Direct effects																		
LN.Age	0.4786	***	(2.9271)	0.2789	***	(3.1646)	0.2718	***	(3.1162)	0.2829	***	(3.2113)	0.2608	***	(2.9249)	0.2642	***	(2.9822)
LN.Age.2	-0.0646	**	-(2.2059)	-0.0335	**	-(2.4147)	-0.0318	**	-(2.3151)	-0.0339	**	-(2.4415)	-0.0304	**	-(2.1669)	-0.0307	**	-(2.1999)
LN.Total.Assets	-0.0453	***	-(6.1363)	-0.0428	***	-(6.0726)	-0.0399	***	-(5.7486)	-0.0436	***	-(6.1405)	-0.0463	***	-(6.6332)	-0.0460	***	-(6.5472)
LN.Total.Assets.2	0.0008	***	(2.7056)	0.0011	***	(3.0824)	0.0009	**	(2.5021)	0.0012	***	(3.2046)	0.0013	***	(3.8287)	0.0013	***	(3.8232)
LN.Age * LN.Total.Assets	0.0010		-(0.4090)	-0.0011		-(0.5133)	-0.0013		-(0.5971)	-0.0011		-(0.4981)	-0.0012		-(0.5239)	-0.0013		-(0.6046)
Syndication.Pipelines.AR.Value.W	0.0262	***	(4.8483)															
Syndication.Pipelines.AR.Count				0.0013	**	(1.9852)												
Syndication.Pipelines.KR.Value.W							0.0231	***	(4.3281)									
Syndication.Pipelines.KR.Count										0.0013		(1.3357)						
Ownership.Pipelines.Value.W													-0.0021		-(0.3519)			
Ownership.Pipelines.Count																-0.0007		-(0.0406)
Survival.Prob	-0.1685	*	-(1.8967)	-0.2051	**	-(2.1149)	-0.2019	**	-(2.1004)	-0.2116	**	-(2.1831)	-0.1882	*	-(1.9242)	-0.1907	*	-(1.9561)
LN.FT.Emp.Own	0.0499	**	(2.0538)	0.0434	**	(2.0655)	0.0436	**	(2.0946)	0.0441	**	(2.1003)	0.0439	**	(2.0726)	0.0428	**	(2.0172)
LN.FT.Emp.Other	-0.0505		-(1.2369)	-0.0647		-(1.3141)	-0.0623		-(1.2781)	-0.0628		-(1.2770)	-0.0656		-(1.3245)	-0.0641		-(1.2953)
Leverage.TLs.To.TAs	0.0021		(0.4685)	0.0005		(0.4155)	0.0005		(0.4348)	0.0005		(0.4051)	0.0004		(0.3421)	0.0004		(0.3452)
Indirect effects																		
W.LN.Age	0.0483		-(0.4029)	-0.0251		-(0.8698)	-0.0100		-(0.3503)	-0.0267		-(0.9268)	-0.0229		-(0.7825)	-0.0201		-(0.6911)
W.LN.Age.2	-0.0084		(0.3050)	0.0037		(0.8149)	0.0014		(0.3203)	0.0041		(0.9115)	0.0034		(0.7486)	0.0032		(0.7054)
W.LN.Total.Assets	0.0014		(0.6352)	0.0007		(0.3892)	0.0010		(0.5970)	-0.0006		-(0.3147)	0.0018		(0.9487)	0.0023		(1.2425)
W.LN.Total.Assets.2	-0.0001		-(0.7217)	-0.0001		-(0.4940)	0.0000		-(0.4201)	0.0001		(0.5116)	-0.0001	.	-(1.5448)	-0.0002	*	-(1.6489)
W.LN.Age * LN.Total.Assets	0.0008		(0.8079)	0.0005		(0.7931)	0.0003		(0.4631)	0.0004		(0.5624)	0.0005		(0.7661)	0.0004		(0.5408)
W.Syndication.Pipelines.AR.Value.W	-0.0061	**	-(2.0635)															
W.Syndication.Pipelines.AR.Count				-0.0004	*	-(1.7593)												
W.Syndication.Pipelines.KR.Value.W							-0.0027	.	-(1.6145)									
W.Syndication.Pipelines.KR.Count										-0.0011	***	-(2.6266)						
W.Ownership.Pipelines.Value.W													-0.0009		-(0.3690)			
W.Ownership.Pipelines.Count																0.0031		(0.3991)
W.Survival.Prob	-0.0397		-(0.1582)	0.0060		(0.2168)	-0.0060		-(0.2199)	0.0116		(0.4189)	0.0034		(0.1229)	0.0011		(0.0384)
W.LN.FT.Emp.Own	-0.0029		-(0.5873)	-0.0010		-(0.6209)	-0.0003		-(0.2085)	-0.0006		-(0.3442)	-0.0003		-(0.1804)	-0.0003		-(0.1948)
W.LN.FT.Emp.Other	0.0049		-(0.1187)	-0.0010		-(0.2498)	-0.0017		-(0.4623)	-0.0022		-(0.5912)	-0.0023		-(0.5955)	-0.0023		-(0.5838)
W.Leverage.TLs.To.TAs	0.0000		(0.2294)	0.0001		(0.2067)	0.0001		(0.2302)	0.0000		(0.1426)	0.0001		(0.1962)	0.0001		(0.2052)
Adjusted pooled R-squared	0.19			0.17			0.18			0.17			0.16			0.16		

Notes: *** significant at 1% level, ** 5% level, * 10% level. Sample period is 2007 - 2015.

Table 5 - Multiply imputed datasets vs hard data

	2009 - 2015						2008 - 2014						2007 - 2013						2007 - 2015					
	MI data			Hard data			MI data			Hard data			MI data			Hard data			MI data			Hard data		
	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat
Direct effects																								
LN.Age	0.4786	***	(3.7971)	0.4931	***	(3.2450)	0.2834	***	(3.0725)	0.4351	***	(3.8760)	0.1622	*	(1.8994)	0.2316	**	(2.1510)	0.2546	***	(2.9271)	0.3367	***	(2.8460)
LN.Age.2	-0.0646	***	-(3.2563)	-0.0745	***	-(3.1010)	-0.0382	***	-(2.6228)	-0.0627	***	-(3.4390)	-0.0186	.	-(1.5677)	-0.0214		-(1.4240)	-0.0302	**	-(2.2059)	-0.0416	**	-(2.3890)
LN.Total.Assets	-0.0453	***	-(4.9786)	-0.0477	***	-(3.9760)	-0.0524	***	-(6.1647)	-0.0508	***	-(4.3420)	-0.0497	***	-(5.8044)	-0.0285	**	-(2.1990)	-0.0420	***	-(6.1363)	-0.0330	***	-(2.9380)
LN.Total.Assets.2	0.0008	*	(1.8294)	0.0009	.	(1.5510)	0.0010	**	(2.3591)	0.0018	***	(2.9400)	0.0013	***	(3.1894)	0.0014	**	(2.3510)	0.0009	***	(2.7056)	0.0012	**	(2.1350)
LN.Age * LN.Total.Assets	0.0010		(0.3288)	0.0035		(0.7750)	0.0014		(0.5195)	-0.0016		-(0.4240)	0.0000		-(0.0097)	-0.0051		-(1.3790)	-0.0009		-(0.4090)	-0.0033		-(0.9920)
Syndication.Pipelines.AR.Value.W	0.0262	***	(3.9592)	0.0143	*	(1.7890)	0.0294	***	(4.7441)	0.0204	***	(2.6710)	0.0235	***	(3.8821)	0.0120	.	(1.5140)	0.0252	***	(4.8483)	0.0179	**	(2.5820)
Survival.Prob	-0.1685	*	-(1.8361)	-0.1712		-(1.4170)	-0.1121		-(1.2750)	-0.1545		-(1.3410)	-0.1406		-(1.0374)	-0.2012		-(1.1250)	-0.1819	*	-(1.8967)	-0.1778		-(1.1680)
LN.FT.Emp.Own	0.0499	**	(2.1073)	0.0367		(1.1130)	0.0340	.	(1.5523)	0.0266		(0.8510)	0.0481	**	(2.1298)	0.0446		(1.2990)	0.0425	**	(2.0538)	0.0554	*	(1.8810)
LN.FT.Emp.Other	-0.0505		-(0.9083)	-0.0815		-(1.0730)	-0.0433		-(0.8062)	0.0102		(0.1370)	-0.0492		-(0.9676)	-0.0024		-(0.0300)	-0.0602		-(1.2369)	0.0247		(0.3370)
Leverage.TLs.To.TAs	0.0021		(0.8795)	0.0070	**	(2.0440)	0.0008		(0.1717)	0.0034		(0.6780)	0.0005		(0.3167)	0.0029		(1.2730)	0.0005		(0.4685)	0.0046	**	(2.1940)
Indirect effects																								
W.LN.Age	0.0483		(1.3807)	0.1844	**	(2.2360)	-0.0026		-(0.0956)	0.1450	**	(2.5320)	0.0059		(0.2405)	0.0782		(1.2420)	-0.0114		-(0.4029)	0.1703	**	(2.3290)
W.LN.Age.2	-0.0084	.	-(1.5677)	-0.0306	**	-(2.1800)	0.0016		(0.3972)	-0.0230	**	-(2.2510)	0.0003		(0.0904)	-0.0080		-(0.8370)	0.0014		(0.3050)	-0.0244	**	-(2.1650)
W.LN.Total.Assets	0.0014		(0.5829)	-0.0106	**	-(2.0310)	0.0024		(1.1540)	-0.0033		-(0.6420)	0.0020		(1.0684)	0.0076		(1.3360)	0.0010		(0.6352)	-0.0033		-(0.6320)
W.LN.Total.Assets.2	-0.0001		-(1.0883)	0.0005	*	(1.9130)	-0.0001		-(0.6786)	0.0005	*	(1.8310)	0.0000		(0.1628)	0.0000		-(0.1280)	-0.0001		-(0.7217)	0.0004		(1.3810)
W.LN.Age * LN.Total.Assets	0.0008		(0.9240)	0.0006		(0.3000)	-0.0001		-(0.1800)	-0.0015		-(0.8450)	-0.0005		-(0.6283)	-0.0015		-(0.8430)	0.0005		(0.8079)	-0.0018		-(1.1400)
W.Syndication.Pipelines.AR.Value.W	-0.0061	***	-(3.2486)	-0.0143	***	-(2.9150)	-0.0043	***	-(2.6909)	-0.0078	*	-(1.8620)	-0.0045	***	-(2.6984)	-0.0076	.	-(1.6310)	-0.0032	**	-(2.0635)	-0.0053		-(1.2990)
W.Survival.Prob	-0.0397	*	-(1.7755)	-0.0901	.	-(1.5910)	-0.0182		-(0.7895)	-0.1026	*	-(1.9190)	-0.0178		-(0.4663)	-0.1466		-(1.4560)	-0.0043		-(0.1582)	-0.1272		-(1.4300)
W.LN.FT.Emp.Own	-0.0029	*	-(1.8778)	0.0029		(0.5390)	0.0006		(0.3878)	-0.0044		-(0.8470)	-0.0005		-(0.3243)	0.0075		(1.0470)	-0.0010		-(0.5873)	0.0029		(0.3840)
W.LN.FT.Emp.Other	0.0049	.	(1.4990)	-0.0039		-(0.2880)	-0.0041		-(1.2781)	0.0145		(1.0560)	-0.0018		-(0.5052)	-0.0206		-(1.1390)	-0.0004		-(0.1187)	0.0097		(0.5470)
W.Leverage.TLs.To.TAs	0.0000		(0.0662)	0.0012		(0.7780)	0.0000		(0.0198)	0.0027		(1.0490)	0.0000		(0.0696)	0.0008		(0.6370)	0.0001		(0.2294)	0.0005		(0.4110)
Adjusted pooled R-squared	0.16			0.22			0.18			0.20			0.14			0.13			0.19			0.26		
Survivors	1351			504			1438			561			1486			438			1246			372		
Sample size (N)	2485			795			2663			810			2830			590			2830			590		

Notes: *** significant at 1% level, ** 5% level, * 10% level

Table 6 - Sensitivity of results to the great circle distance used for W specification

	20 km			30 km			40 km			50 km			60 km			70 km			80 km		
	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat
Direct effects																					
LN.Age	0.4108	***	(3.1964)	0.3688	***	(2.8454)	0.4555	***	(3.5134)	0.4786	***	(3.7971)	0.4759	***	(3.7670)	0.4606	***	(3.6807)	0.4395	***	(3.5049)
LN.Age.2	-0.0513	**	-(2.5243)	-0.0481	**	-(2.3654)	-0.0625	***	-(3.0714)	-0.0646	***	-(3.2563)	-0.0637	***	-(3.1933)	-0.0645	***	-(3.2561)	-0.0604	***	-(3.0448)
LN.Total.Assets	-0.0464	***	-(4.9543)	-0.0443	***	-(4.8043)	-0.0491	***	-(5.2162)	-0.0453	***	-(4.9786)	-0.0472	***	-(5.1134)	-0.0462	***	-(4.8214)	-0.0527	***	-(5.6542)
LN.Total.Assets.2	0.0010	**	(2.1980)	0.0008	*	(1.7403)	0.0009	**	(2.0220)	0.0008	*	(1.8294)	0.0010	**	(2.2404)	0.0006		(1.2585)	0.0009	*	(1.8921)
LN.Age * LN.Total.Assets	-0.0004		-(0.1399)	0.0009		(0.2946)	0.0013		(0.4460)	0.0010		(0.3288)	0.0004		(0.1163)	0.0029		(0.9454)	0.0027		(0.8769)
Syndication.Pipelines.AR.Value.W	0.0313	***	(4.7614)	0.0281	***	(4.2681)	0.0282	***	(4.2684)	0.0262	***	(3.9592)	0.0280	***	(4.2133)	0.0268	***	(3.9648)	0.0279	***	(4.1832)
Survival.Prob	-0.1335	.	-(1.4403)	-0.1028		-(1.1024)	-0.1261		-(1.3314)	-0.1685	*	-(1.8361)	-0.1685	*	-(1.8266)	-0.1553	*	-(1.6988)	-0.1354	.	-(1.4749)
LN.FT.Emp.Own	0.0438	*	(1.8400)	0.0206		(0.9215)	0.0469	**	(2.0335)	0.0499	**	(2.1073)	0.0530	**	(2.2745)	0.0482	**	(2.1300)	0.0390	*	(1.7638)
LN.FT.Emp.Other	-0.0074		-(0.1543)	0.0310		(0.5865)	-0.0250		-(0.4552)	-0.0505		-(0.9083)	-0.0674		-(1.1927)	-0.0621		-(1.0568)	-0.0409		-(0.7384)
Leverage.TLs.To.TAs	0.0020		(0.7822)	0.0019		(0.7858)	0.0017		(0.6779)	0.0021		(0.8795)	0.0018		(0.7187)	0.0022		(0.9072)	0.0019		(0.7955)
Indirect effects																					
W.LN.Age	-0.0830	.	-(1.5604)	-0.1039	**	-(2.0662)	-0.0033		-(0.0781)	0.0483		(1.3807)	0.0302		(0.8972)	-0.0088		-(0.2802)	-0.0278		-(0.9277)
W.LN.Age.2	0.0143	*	(1.7733)	0.0147	**	(1.9772)	-0.0019		-(0.2930)	-0.0084	.	-(1.5677)	-0.0052		-(1.0287)	-0.0023		-(0.4942)	0.0018		(0.4042)
W.LN.Total.Assets	-0.0007		-(0.2849)	0.0011		(0.4432)	-0.0040	.	-(1.5794)	0.0014		(0.5829)	-0.0017		-(0.6677)	-0.0005		-(0.1996)	-0.0057	**	-(2.3245)
W.LN.Total.Assets.2	0.0000		(0.2731)	-0.0001		-(1.4123)	0.0000		(0.4464)	-0.0001		-(1.0883)	0.0001		(1.1503)	-0.0003	**	-(2.3537)	0.0000		-(0.3102)
W.LN.Age * LN.Total.Assets	-0.0001		-(0.0899)	0.0009		(0.9696)	0.0011		(1.2421)	0.0008		(0.9240)	0.0001		(0.1256)	0.0025	**	(2.5321)	0.0021	**	(2.1928)
W.Syndication.Pipelines.AR.Value.W	0.0001		(0.0523)	-0.0035	*	-(1.8139)	-0.0038	**	-(2.0817)	-0.0061	***	-(3.2486)	-0.0047	**	-(2.3614)	-0.0045	**	-(2.1344)	-0.0030	.	-(1.5927)
W.Survival.Prob	0.0408		(1.1889)	0.0616	*	(1.8822)	0.0300		(1.0925)	-0.0397	*	-(1.7755)	-0.0185		-(0.8080)	0.0078		(0.3441)	0.0337	.	(1.5429)
W.LN.FT.Emp.Own	0.0009		(0.4685)	-0.0035	**	-(2.0563)	0.0001		(0.0833)	-0.0029	*	-(1.8778)	-0.0007		-(0.5233)	-0.0026	*	-(1.8230)	0.0016		(1.1976)
W.LN.FT.Emp.Other	0.0011		(0.2637)	0.0074	**	(2.1159)	0.0020		(0.5830)	0.0049	.	(1.4990)	0.0021		(0.7779)	0.0042	.	(1.4870)	-0.0016		-(0.5987)
W.Leverage.TLs.To.TAs	0.0000		(0.0075)	-0.0001		-(0.2224)	-0.0004		-(0.5563)	0.0000		(0.0662)	-0.0002		-(0.2718)	0.0003		(0.5335)	-0.0001		-(0.2112)

Notes: *** significant at 1% level, ** 5% level, * 10% level; 20 - 80km in the top row are the great circle distances used to select neighbours for the binary adjacency spatial weights matrix W. Sample period is 2009 - 2015.

Table 7 - The London effect

	2009 - 2015						2008 - 2014						2007 - 2013						2007 - 2015					
	[1]			[2]			[3]			[4]			[5]			[6]			[7]			[8]		
	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat	β	***	t-stat
Direct effects																								
LN.Age	0.4786	***	(3.7971)	0.4656	***	(3.6013)	0.2834	***	(3.0725)	0.2816	***	(2.9705)	0.1622	**	(1.8994)	0.1668	*	(1.9395)	0.2546	***	(2.9271)	0.2560	***	(2.8828)
LN.Age.2	-0.0646	***	-(3.2563)	-0.0634	***	-(3.1138)	-0.0382	***	-(2.6228)	-0.0380	**	-(2.5433)	-0.0186	.	-(1.5677)	-0.0193	.	-(1.6147)	-0.0302	**	-(2.2059)	-0.0308	**	-(2.1846)
LN.Total.Assets	-0.0453	***	-(4.9786)	-0.0463	***	-(5.0423)	-0.0524	***	-(6.1647)	-0.0527	***	-(6.1624)	-0.0497	***	-(5.8044)	-0.0495	***	-(5.7237)	-0.0420	***	-(6.1363)	-0.0422	***	-(6.1120)
LN.Total.Assets.2	0.0008	*	(1.8294)	0.0008	*	(1.7636)	0.0010	**	(2.3591)	0.0010	**	(2.3597)	0.0013	***	(3.1894)	0.0013	***	(3.1887)	0.0009	***	(2.7056)	0.0009	***	(2.6515)
LN.Age * LN.Total.Assets	0.0010		(0.3288)	0.0016		(0.5064)	0.0014		(0.5195)	0.0014		(0.5373)	0.0000		-(0.0097)	-0.0001		-(0.0282)	-0.0009		-(0.4090)	-0.0007		-(0.3021)
Syndication.Pipelines.AR.Value.W	0.0262	***	(3.9592)	0.0413	***	(3.0406)	0.0294	***	(4.7441)	0.0415	***	(3.3896)	0.0235	***	(3.8821)	0.0371	***	(3.1664)	0.0252	***	(4.8483)	0.0365	***	(3.5671)
Syndication.Pipelines * London				-0.0188		-(1.2910)				-0.0150		-(1.1050)				-0.0171		-(1.3123)				-0.0142		-(1.2555)
London				-0.0677		-(1.1535)				-0.0132		-(0.2246)				0.0178		(0.3104)				-0.0242		-(0.4451)
Survival.Prob	-0.1685	*	-(1.8361)	-0.1619	*	-(1.7292)	-0.1121		-(1.2750)	-0.1101		-(1.2282)	-0.1406		-(1.0374)	-0.1470		-(1.0793)	-0.1819	*	-(1.8967)	-0.1834	*	-(1.8776)
LN.FT.Emp.Own	0.0499	**	(2.1073)	0.0523	**	(2.1573)	0.0340	.	(1.5523)	0.0327	.	(1.4384)	0.0481	**	(2.1298)	0.0485	**	(2.0922)	0.0425	**	(2.0538)	0.0413	*	(1.9414)
LN.FT.Emp.Other	-0.0505		-(0.9083)	-0.0291		-(0.4543)	-0.0433		-(0.8062)	-0.0358		-(0.5487)	-0.0492		-(0.9676)	-0.0566		-(0.9251)	-0.0602		-(1.2369)	-0.0460		-(0.7898)
Leverage.TLs.To.TAs	0.0021		(0.8795)	0.0020		(0.8617)	0.0008		(0.1717)	0.0009		(0.1795)	0.0005		(0.3167)	0.0005		(0.3324)	0.0005		(0.4685)	0.0006		(0.5017)
Indirect effects																								
W.LN.Age	0.0483		(1.3807)	0.0378		(0.8778)	-0.0026		-(0.0956)	-0.0045		-(0.1343)	0.0059		(0.2405)	0.0107		(0.4050)	-0.0114		-(0.4029)	-0.0119		-(0.3627)
W.LN.Age.2	-0.0084	.	-(1.5677)	-0.0072		-(1.0701)	0.0016		(0.3972)	0.0020		(0.3795)	0.0003		(0.0904)	-0.0002		-(0.0659)	0.0014		(0.3050)	0.0014		(0.2541)
W.LN.Total.Assets	0.0014		(0.5829)	0.0007		(0.2965)	0.0024		(1.1540)	0.0024		(1.0372)	0.0020		(1.0684)	0.0024		(1.0646)	0.0010		(0.6352)	0.0009		(0.5002)
W.LN.Total.Assets.2	-0.0001		-(1.0883)	-0.0001		-(1.0666)	-0.0001		-(0.6786)	-0.0001		-(0.6100)	0.0000		(0.1628)	0.0000		(0.2235)	-0.0001		-(0.7217)	-0.0001		-(0.6591)
W.LN.Age * LN.Total.Assets	0.0008		(0.9240)	0.0011		(1.2250)	-0.0001		-(0.1800)	-0.0002		-(0.2230)	-0.0005		-(0.6283)	-0.0006		-(0.7780)	0.0005		(0.8079)	0.0005		(0.7602)
W.Syndication.Pipelines.AR.Value.W	-0.0061	***	-(3.2486)	-0.0058	**	-(2.3214)	-0.0043	***	-(2.6909)	-0.0048	**	-(2.4021)	-0.0045	***	-(2.6984)	-0.0052	***	-(2.7043)	-0.0032	**	-(2.0635)	-0.0035	*	-(1.8170)
W.Syndication.Pipelines * London				-0.0007		-(0.3281)				0.0008		(0.3794)				0.0010		(0.5693)				0.0003		(0.1778)
W.London				0.0004		(0.1191)				0.0001		(0.0400)				0.0000		(0.0010)				0.0004		(0.1216)
W.Survival.Prob	-0.0397	*	-(1.7755)	-0.0358		-(1.3341)	-0.0182		-(0.7895)	-0.0167		-(0.5860)	-0.0178		-(0.4663)	-0.0251		-(0.6090)	-0.0043		-(0.1582)	-0.0039		-(0.1251)
W.LN.FT.Emp.Own	-0.0029	*	-(1.8778)	-0.0030	*	-(1.8322)	0.0006		(0.3878)	0.0005		(0.3187)	-0.0005		-(0.3243)	-0.0007		-(0.3465)	-0.0010		-(0.5873)	-0.0009		-(0.4336)
W.LN.FT.Emp.Other	0.0049	.	(1.4990)	0.0049		(1.3463)	-0.0041		-(1.2781)	-0.0040		-(1.1473)	-0.0018		-(0.5052)	-0.0013		-(0.3471)	-0.0004		-(0.1187)	-0.0008		-(0.1980)
W.Leverage.TLs.To.TAs	0.0000		(0.0662)	0.0001		(0.1019)	0.0000		(0.0198)	0.0000		(0.0293)	0.0000		(0.0696)	0.0000		(0.0790)	0.0001		(0.2294)	0.0001		(0.2495)
Adjusted pooled R-squared	0.16			0.16			0.18			0.18			0.14			0.14			0.19			0.19		

Notes: *** significant at 1% level, ** 5% level, * 10% level

Discussion

The primary objective of this paper has been to study the links between inter-cluster network connections of financial services firms, their long-term growth rate and the associated spillovers to other financial services firms in their proximity. To isolate this effect from other potential sources of spatial spillovers, such as labour force pooling and input-output linkages, we also controlled for localisation and urbanisation economies, represented by own and other sector employment. Our results indicate that clustering of employment in own sector leads to higher firm growth. This supports the existence of Marshall – Arrow – Romer (MAR) spillovers (Marshall, 1920; Arrow, 1962; Romer, 1986) and is consistent with much of the empirical literature on the topic (Swann et al., 1998; Pandit et al., 2001; Fingleton et al., 2004; Cook et al., 2007; Beaudry & Swann, 2009; Eriksson, 2011). In contrast, we did not find any significant effect of urbanisation economies, measured by other sector employment, on firm growth. This is not entirely surprising as others have reported similar results in the context of financial services (Pandit et al., 2001) or their results imply that co-location of firms from different industries has both positive and negative effects on the desirability of a location (Cook et al., 2007).

Our results paint a picture of substantial heterogeneity within clusters. Bathelt et al. (2004) predict that global pipelines should enhance the competitiveness and growth of clusters, an effect enhanced by network connectivity within clusters and limited by the absorptive capacity of firms. We find that the connected firms generally benefit from forming global pipelines and this effect varies with the size of FCs they are connected to. On the other hand, the observed spatial spillovers are overwhelmingly negative and can be interpreted as a growth of connected firms at the expense of others in their proximity, due to the widening gap in their knowledge bases. Our results indicate that there is a 0.31% to 0.61% decrease in the average annual firm growth rate per one standard deviation increase in the value-weighted syndication pipelines of a single firm in the cluster. This implies that on average connected firms behave more like external stars than gatekeepers of knowledge and restrict any valuable knowledge transfers within their cluster (Giuliani, 2007, 2011; Morrison, 2008; Lazaric et al., 2008). Consequently, the gap between the knowledge bases and competitiveness of the most and least connected firms widens, leading to a divergence in their growth rates. This is consistent with the simulation results of Cowan and Jonard (2004) on knowledge transfers in networks, who found that an equilibrium condition with mostly local and small number of extra-local connections (‘small world’) would lead to high variance of knowledge levels. Consequently, firms with inter-cluster network connections would be expected to perform better ceteris paribus, as has been shown in our results. Our results also extend those of Eisingerich et al. (2010), who show that network openness leads to higher performance of clusters, by adding that this effect varies throughout the cluster and in fact impedes the growth of firms located in the cluster, but lacking inter-cluster connections.

The primary contribution of this paper to the existing literature is the empirical analysis of the links between global pipelines, knowledge spillovers and firm growth. We focus on financial services firms, which have been particularly sparsely researched in this context, while there is a fairly substantial empirical evidence available on knowledge transfers and spillovers regarding high-technology firms from a variety of industries (Swann et al., 1998;

Stuart, 2000; Fingleton et al., 2004; Trippl et al., 2009). This paper furthers the work of studies such as that of Pandit et al. (2001), by adding a specific source of knowledge transfers and spillovers to the functional form of econometric models and by allowing for much more direct econometric modelling of spatial spillovers by using spatial econometric techniques, instead of using non-spatial lifetime growth models, which have become a popular choice in related studies (Swann et al., 1998; Pandit et al., 2001; Beaudry and Swann, 2009). Although the methods used here are not new, their unique combination and application in this context breaks a new ground and will hopefully inspire future research on financial centres based on micro-economic level of analysis and the use of spatial econometric techniques, which open large number of potential directions for further research. Our results also underline the value of researching economic-geographical phenomena at firm level, given that simply looking at the net effect of knowledge transfers at the level of clusters or regions can often overlook important heterogeneity observable only at the firm level – such as the differing effects of global pipelines on connected firms and other firms in their proximity.

Our work is restricted to England, Scotland, and Wales and although we focus on long-term firm growth, we use at most eight years of data. With better data availability in the future, this research can hopefully be extended to cover longer-time periods and more countries. More work needs to be done to identify the channels through which knowledge flows within clusters and how they impact on the spillovers affecting nearby firms. It is plausible that some firms in the cluster may benefit from knowledge transfers with connected firms, while others may experience negative spillovers due to increased competitive pressures. Finally, our analysis is subject to the usual caveats regarding the use of partial correlations in studying causal relationships. Nevertheless, a case has been made here for why a causal relationship is likely to exist between inter-cluster network connections and firm growth. We hope that future research will build on this contribution.

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Appendix

A.1

Variable definitions and data sources

Variable name	Definition	Data source
G_TA_t_t+j	Average annual growth rate in total assets for the stated time period, where j is either six or eight years.	Authors' calculations based on FAME data
LN.Age	Natural logarithm of firm age in years	FAME
LN.Age.2	Square of natural logarithm of firm age	FAME
LN.Total.Assets	Natural logarithm of total assets (th GBP)	FAME
LN.Total.Assets.2	Square of natural logarithm of total assets (th GBP)	FAME
Survival.Prob	Probit estimate of survival probability for the given time period	Estimates based on FAME data
LN.FT.Emp.Own	Natural logarithm of full time employment in financial services	BRES - ONS
LN.FT.Emp.Other	Natural logarithm of full time employment in all industries other than financial services	BRES - ONS
Leverage.TLs.To.TAs	Leverage (total liabilities to total assets)	FAME
London	Binary indicator variable; = 1 if NUTS1 region is the Greater London and = 0 otherwise	FAME (conversion from postcodes to NUTS regions)
Syndication.Pipelines.AR.Value.W	Sum of value weighted syndication links to firms in other financial centres during the 3 years before the beginning of the time frame modelled. Each financial centre is only counted once and the links are weighted by the aggregate fees earned from the four products (ECM, DCM, LOANS, M&As) considered here by firms in this financial centre in the year preceding the beginng of the time period modelled. This variable is then converted to a z-score by subtracting mean and diving it by its standard deviation.	Dealogic (authors' calculations)
Syndication.Dom.Pipelines.AR.Value.W	Same as Syndication.Pipelines.AR.Value.W, but only links to financial centres within Great Britain are considered.	Dealogic
Syndication.CB.Pipelines.AR.Value.W	Same as Syndication.Pipelines.AR.Value.W, but only links to financial centres outside of Great Britain are considered.	Dealogic
Syndication.Pipelines.AR.Count	Same as Syndication.Pipelines.AR.Value.W, but only a count of unique links to other financial centres is considered, without the subsequent weighting by aggregate city fees.	Dealogic
Syndication.Pipelines.KR.Value.W	Same as Syndication.Pipelines.AR.Value.W, but only syndication links between advisors in lead roles are considered. This means that any co-managemenet or lower appointments are omitted from the analysis.	Dealogic
Syndication.Pipelines.KR.Count	Same as Syndication.Pipelines.KR.Value.W, but only a count of unique links to other financial centres is considered, without the subsequent weighting by aggregate city fees.	Dealogic
Ownership.Pipelines.Count	Number of unique links to other cities through the ownership of subsidiaries in these cities.	FAME
Ownership.Pipelines.Value.W	Number of unique links to other cities through the ownership of subsidiaries in these cities weighted by the fees earned from ECM, DCM, LOANS and M&As by financial services in the city in the year preceding the beginning of the time period considered.	FAME, Dealogic

Source: FAME, Dealogic, ONS-BRES

A.2

Descriptive statistics

Variable name	Time period	Observations	Missing	Min	Median	Mean	Max	SD
G_TA_2007_2015	2007 - 2015	1,246	1,584	-1.58	-0.02	-0.01	1.85	0.24
G_TA_2007_2013	2007 - 2013	1,486	1,344	-2.10	-0.01	-0.01	1.98	0.28
G_TA_2008_2014	2008 - 2014	1,438	1,225	-2.10	0.00	0.00	2.46	0.28
G_TA_2009_2015	2009 - 2015	1,351	1,134	-2.10	-0.01	-0.01	2.47	0.28
Age	2007 - 2015	2,829	1	0.00	1.00	7.01	142.00	13.86
	2007 - 2013	2,829	1	0.00	1.00	7.01	142.00	13.86
	2008 - 2014	2,663	0	0.00	2.00	8.53	143.00	14.26
	2009 - 2015	2,483	2	0.00	5.00	10.13	144.00	14.70
Total.Assets.th.GBP	2007 - 2015	2,829	1	1	215	6,027,389	1,689,308,000	68,867,463
	2007 - 2013	2,829	1	1	215	6,027,389	1,689,308,000	68,867,463
	2008 - 2014	2,663	0	1	299	6,186,411	1,612,822,000	68,725,892
	2009 - 2015	2,483	2	1	450	7,143,568	1,656,437,000	78,685,140
Survival.Prob	2007 - 2015	2,829	1	0.00	0.17	0.43	1.00	0.43
	2007 - 2013	2,829	1	0.02	0.44	0.53	1.00	0.38
	2008 - 2014	2,663	0	0.00	0.50	0.54	1.00	0.41
	2009 - 2015	2,483	2	0.00	0.59	0.53	1.00	0.41
FT.Emp.Own	2007 - 2015	2,829	1	1,748	31,321	132,648	251,399	114,538
	2007 - 2013	2,829	1	1,748	31,321	132,648	251,399	114,538
	2008 - 2014	2,663	0	1,689	256,332	140,841	256,332	117,121
	2009 - 2015	2,483	2	1,471	240,199	137,519	240,199	108,732
FT.Emp.Other	2007 - 2015	2,829	1	118,292	1,131,282	1,118,582	1,607,369	509,767
	2007 - 2013	2,829	1	118,292	1,131,282	1,118,582	1,607,369	509,767
	2008 - 2014	2,663	0	114,080	1,656,539	1,167,723	1,656,539	529,661
	2009 - 2015	2,483	2	113,814	1,696,362	1,202,632	1,696,362	551,185
Leverage.TLs.To.TAs	2007 - 2015	589	2,241	-0.19	0.71	1.12	67.38	3.96
	2007 - 2013	589	2,241	-0.19	0.71	1.12	67.38	3.96
	2008 - 2014	810	1,853	-0.30	0.73	1.52	225.00	11.21
	2009 - 2015	793	1,692	-0.23	0.73	1.30	213.00	8.02
London	2007 - 2015	2,829	1	0.00	1.00	0.58	1.00	0.49
	2007 - 2013	2,829	1	0.00	1.00	0.58	1.00	0.49
	2008 - 2014	2,663	0	0.00	1.00	0.59	1.00	0.49
	2009 - 2015	2,483	2	0.00	1.00	0.61	1.00	0.49
Syndication.Pipelines.AR.Value.W	2007 - 2015	2,829	1	-0.27	-0.27	0.00	5.44	1.00
	2007 - 2013	2,829	1	-0.27	-0.27	0.00	5.44	1.00
	2008 - 2014	2,663	0	-0.29	-0.29	0.00	5.30	1.00
	2009 - 2015	2,483	2	-0.31	-0.31	0.00	5.26	1.00
Syndication.Dom.Pipelines.AR.Value.W	2007 - 2015	2,829	1	-0.31	-0.31	0.00	3.53	1.00
	2007 - 2013	2,829	1	-0.31	-0.31	0.00	3.53	1.00
	2008 - 2014	2,663	0	-0.34	-0.34	0.00	3.27	1.00
	2009 - 2015	2,483	2	-0.35	-0.35	0.00	3.01	1.00
Syndication.CB.Pipelines.AR.Value.W	2007 - 2015	2,829	1	-0.25	-0.25	0.00	5.56	1.00
	2007 - 2013	2,829	1	-0.25	-0.25	0.00	5.56	1.00
	2008 - 2014	2,663	0	-0.26	-0.26	0.00	5.47	1.00
	2009 - 2015	2,483	2	-0.27	-0.27	0.00	5.60	1.00
Syndication.Pipelines.AR.Count	2007 - 2015	2,829	1	0.00	0.00	1.24	123.00	7.93
	2007 - 2013	2,829	1	0.00	0.00	1.24	123.00	7.93
	2008 - 2014	2,663	0	0.00	0.00	1.35	126.00	8.12
	2009 - 2015	2,483	2	0.00	0.00	1.38	138.00	8.25
Syndication.Pipelines.KR.Value.W	2007 - 2015	2,829	1	-0.24	-0.24	0.00	7.11	1.00
	2007 - 2013	2,829	1	-0.24	-0.24	0.00	7.11	1.00
	2008 - 2014	2,663	0	-0.26	-0.26	0.00	6.96	1.00
	2009 - 2015	2,483	2	-0.30	-0.30	0.00	6.60	1.00
Syndication.Pipelines.KR.Count	2007 - 2015	2,829	1	0.00	0.00	0.68	114.00	5.60
	2007 - 2013	2,829	1	0.00	0.00	0.68	114.00	5.60
	2008 - 2014	2,663	0	0.00	0.00	0.77	119.00	5.94
	2009 - 2015	2,483	2	0.00	0.00	0.85	127.00	6.30
Ownership.Pipelines.Value.W	2007 - 2015	2,829	1	-0.04	-0.04	0.00	34.82	1.00
	2007 - 2013	2,829	1	-0.04	-0.04	0.00	34.82	1.00
	2008 - 2014	2,663	0	-0.03	-0.03	0.00	39.97	1.00
	2009 - 2015	2,483	2	-0.05	-0.05	0.00	29.16	1.00
Ownership.Pipelines.Count	2007 - 2015	2,829	1	0.00	0.00	0.02	13.00	0.38
	2007 - 2013	2,829	1	0.00	0.00	0.02	13.00	0.38
	2008 - 2014	2,663	0	0.00	0.00	0.01	10.00	0.33
	2009 - 2015	2,483	2	0.00	0.00	0.02	10.00	0.34

Source: Authors' calculations based on Dealogic, FAME, ONS-BRES data

A.3

The four equations below further specify the structure of our proxy variables for global pipelines:

$SP_i = \sum_1^N D_n$ (3)

where SPi is the syndication pipelines count variable, Dn is a binary indicator variable (=1 if company i had formed a syndicate within the three years preceding the beginning of the modelled period with another company in city n, and =0 otherwise). The distinction between ‘all roles’ and ‘key roles’ versions of this variable is in the underlying data used to construct this variable, which features all members of the syndicate in the former case and only lead managers in the latter.

$SPVW_i = \sum_1^N (D_n * S_n)$ (4)

where SPVWi is the value-weighted syndication pipelines variable, Dn is defined as above, and Sn is the value of fees earned by advisors in city n in the year immediately preceding the beginning of the modelled period.

$OP_i = \sum_1^N D'_n$ (5)

where OPi is the ownership pipelines count variable, D'_n is a binary indicator variable, which =1 if company i owns a subsidiary in city n and =0 otherwise.

$OPVW_i = \sum_1^N (D'_n * S_n)$ (6)

where OPVWi is the value-weighted ownership pipelines count variable, with D'_n and Sn defined the same way as above.