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Banks, industrial relatedness and firms' investments

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Abstract

In this paper, we study whether industrial relatedness affects firms' fixed investment behaviour, and whether this relationship is linked also to the operational and organizational proximity between banks and local economies. By estimating different specifications of a dynamic investment equation on an unbalanced panel of Italian manufacturing firms for the period 2000-2007, we find that industrial relatedness boosts fixed investments by lowering their sensitivity to cash flow. This occurs because in technologically related areas banks benefit from lower screening and monitoring costs, easier re-allocation of property rights, and higher likelihood of establishing extended credit relationships with firms. However, we find also that the positive effect of industrial relatedness on investments disappears as the functional distance between local branches and their headquarters increases: more hierarchical and less embedded banks find it more difficult to collect tacit information on inter-firm production and financial linkages at the local level and therefore reduce credit provision.

Keywords: error correction model, fixed investments, industrial relatedness, functional distance, operational proximity

JEL: G21, G34, L60, O12, R51

1. Introduction

Real investments in fixed capital assets are a key factor for economic growth: they are both a symptom and a cause of firm expansion; they are an input to the innovation process and they represent a form of capital embodied technological change. The realization of investments depends crucially on credit availability, and, in turn, credit depends on the development of the (local) banking system and its capability to acquire relevant information on borrowing firms.

In this paper we investigate whether firm level investments are also affected by the degree of industry relatedness (IR) in the surrounding local area. Specifically, we ask whether location in a technologically related area makes it easier for banks to decrease credit rationing so as to favour an increase in firms' fixed investments rates.

According to the literature on small business lending (Petersen and Rajan, 2002; Berger and Udell, 2002; Giroud, 2013), banks are more likely to lend to local borrowers because spatial proximity reduces information asymmetries and facilitates monitoring. The role of proximity is particularly relevant when banks collect soft information. Recent works distinguish between two types of proximity: operational and functional (Alessandrini *et al.*, 2009, 2010). The former relates to the spatial density of local branches within a geographic area, while the latter relates to banks' hierarchical structures, measured according to the number of decisional layers between the local branch (where information is collected) and the headquarters (where final decisions are taken). According to this literature, higher operational proximity should favour investments and small business lending by reducing credit rationing. In contrast, a higher functional distance between a local branch and its headquarter does have a negative effect on business lending.

In this paper, we introduce another form of spatial proximity, i.e. IR, which can induce banks to release credit and stimulate the accumulation of fixed capital assets by firms. There are three possible explanations for the link between a higher level of IR and lower credit rationing, measured as cash flow sensitivity of investments.[1]

First, according to works on asymmetric information, higher IR reduces sectoral heterogeneity and makes it easier for banks to evaluate investment projects both *ex-ante*, through screening, and *ex-post*, through monitoring (Baffigi *et al.*, 2000; Pagnini, 2000).

Second, according to the literature on property rights and contractual incompleteness (Hart, 1995), higher IR should favour the re-allocation of property rights in the case of insolvency among the parties. This is due to the more efficient circulation of tacit information and a dense network of

[1] Following Alessandrini *et al.* (2009), we would expect a financially constrained firm to exhibit a positive correlation between cash flow and investment. For a critique of the use of investment-cash flow sensitivity as a measure of credit rationing see Kaplan and Zingales (1997).

horizontal and vertical linkages among firms and suppliers which make it easier for lenders to re-utilize the dismissed capital assets in the case of a negative productivity shock. However, the soft and tacit nature of knowledge, information and production relationships combined with higher vulnerability in the case of systemic failures (Cainelli *et al.*, 2012), makes firms located in technologically related systems less eligible for credit than firms located elsewhere.

Third, the industrial districts literature (Dei Ottati, 1994) emphasizes that, in highly related local systems, bank-firm credit relationships are stronger than in unrelated areas. A firm located within an industrially related area is part of a dense network of relationships that involves the labour market, the various production stages within the value chain, and the local provision of credit. This last may take the form of relationship lending where financial credits are strictly related to subcontracting linkages between buyers and suppliers. In this case, the credit provided by a bank to a firm fosters a series of additional credits – often unknown to the bank – between the firm and its sub-contractors and suppliers. This IR can spur or hamper investments by influencing credit rationing. On the one hand, banks find it more difficult to collect tacit information in highly related areas because of higher information asymmetries with respect to borrowers, and because of a higher systemic risk from unexpected negative shocks. This will apply particularly to banks not embedded in the local system (i.e. non-local banks) or banks characterized by higher organizational complexity (i.e. functional distance). On the other hand, banks may release more credit because firms in technologically related areas find cheating behaviour (or the idea of changing credit providers) less profitable: moving to another bank or deviating from a credit contract damages the net of suppliers linked to the firm at both the production and financial levels.

In the context of this framework, we would expect, all things being equal, that fixed investments will be less sensitive to cash flow the higher the degree of IR in the area of the firm's location, and the lower the operational and functional distance among banks.

2. Dataset and empirical modelling

2.1. Dataset

Our empirical investigation is based on an original firm level dataset built by matching three different statistical sources. The first source is AIDA: a commercial database, collected by *Bureau Van Dijk*, which provides balance sheet information for more than 200,000 Italian joint stock companies. From this source, we draw information to construct our main firm-level variables: fixed investment, capital stock and cash-flow. Firm investment at current prices ($IC_{i,t}$) is computed as: $IC_{i,t} = TA_{i,t} - TA_{i,t-1} + A_{i,t}$ where TA denotes tangible assets and A allowances. The replacement values of the capital stock ($K_{i,t}$) is obtained using the perpetual inventory method, giving $K_{i,t} = K_{i,t-1}(1-\delta)(p_t^I / p_{t-1}^I) + I_{i,t}$ where δ is the depreciation rate set at 0.085, p_t^I is the price of investment goods drawn from the National Accounts and I_t is the investment level in real terms at time *t*.[2] Cash-flow ($CF_{i,t}$) is computed as post-tax plus depreciation of fixed assets, the latter included as a proxy for financial constraints (Fazzari *et al.*, 1988; Kaplan and Zingales, 1997). In order to avoid outlying observations, we slightly trimmed (0.5% of both tails of the distributions) $\frac{I_{i,t}}{K_{i,t-1}}$. This generated an unbalanced panel dataset of 13,000 manufacturing firms (and more than 70,000 observations) for the period 2000-2007. Table 1 presents the structure of the sample according to firm size, area and industry.

[TABLE 1 about here]

The second statistical source used in this paper is the Bank of Italy's database of the Italian banking system, which provides at municipality level information on the number of bank branches by bank type. We aggregate these data at the Local Labour System (LLS) level, adopting the official ISTAT's (ISTAT, 1997) definition. Following Alessandrini *et al.* (2009, 2010), we use this information to develop two different indicators to capture the degree of development, and organization of the Italian banking system: (i) an indicator of operational proximity and (ii) an indicator of functional distance. Operational proximity (OP) is based on the branch density in each local system and is computed as follows:

[2] $$OP_{st} = \frac{\sum_{k_{st}} \text{branches}_{k_{st}}}{\text{population}_{st}} * 10{,}000$$

where k_{st} is the number of branches located in the LLS s in the year *t*, and population_{st} indicates the corresponding population level.

Functional distance (FD) is a proxy for the 'organizational' distance between local branches and their headquarters. To compute this indicator we classify Italian banks according to a set of characteristics such as size (number of branches), juridical status, ownership structure and

[2] Since the book values of fixed capital for the first year of observation (1998) are expressed in historical prices, we multiplied the values by a factor of 1.251 to account for inflation. This provides estimates of corresponding replacement values.

membership of a business group. We also consider an organizational model in relation to four different hierarchical structures. At the extreme low of the range, is the hierarchical organization of BCCs (*Banche di Credito Cooperativo*) or small banks, which is characterized by four decision levels, from the local bank manager with relatively high decision making autonomy, who shares a common set of knowledge with the local communities, to the large banks (with more than 300 branches), which have around ten hierarchical levels. In most cases, managers of large bank branches are responsible only for preliminary screening of loan applications following well-defined, standardized rules, based mainly on hard information. Depending on the amount and importance of a loan, the investment project passes through nine additional steps before the final decision. Monitoring of loan performance is often centralized and in large bank branches there may be frequent turnover of local managers. Between these two extremes, are two intermediate structures with respectively six and eight decisional levels.[3]

Each branch k located in the LLS s is associated with its hierarchical model as follows:

$$[3] \quad FD_{st} = \frac{\sum_{k_{st}} (\text{branches}_{k_{st}} * number - of - hierarchical - levels)_{st}}{\sum_{k_{st}} (\text{branches}_{k_{st}})} .$$

Figure 1 shows the geographical quintile distribution of OP and FD in 2007, where the darker areas indicate higher operational proximity and lower functional distance.

[FIGURE 1 about here]

The third statistical source is the Italian Industry Census, provided by the Italian National Statistical Institute (ISTAT), which we used to calculate our IR variable. Following Frenken *et al.* (2007) and using employment data at the five-digit level, we compute this indicator for the year 1991 for each LLS as follows:

[3] E.g. eight levels correspond to: board of directors, general director, executive committee, administrative director, area director, DAT, branch manager, branch loan officer. Six levels correspond to: board of director, general director, administrative director, area director, DAT, branch manager.

[4] $RV_{s,1991} = \sum_{g=1}^{G} P_g H_g$

where $H_g = \sum_{i \in S_g} \frac{p_i}{P_g} \log_2 \left(\frac{P_g}{p_i} \right)$, S_g indicates each two-digit sector, g=1,…,G are the five-digit sectors, P_g is the two-digit share calculated as the sum of five-digit shares, $P_g = \sum_{i \in S_g} p_i$ and $RV_{s,1991}$ represents a weighted sum of entropy within each two-digit sector.

Finally, we introduce in our specifications a dummy variable ($District_s$) which takes the value 1 if the LLS is classified as an industrial district according to the ISTAT-Sforzi algorithm (ISTAT, 1997) and 0 otherwise. This dummy is added to control for the particular nature of industrial districts, as local production systems characterized by high specialization and the presence of a strong network of inter-firm linkages which a predominance of small-sized firms (Signorini, 2000; Cainelli, 2008).

2.2. The empirical modelling

To test our hypotheses, we estimate an Error Correction Model (ECM) for investments in new capital assets,[4] augmented to include bank-level variables for functional and operational proximity, and their interaction with related variety at the local level. Assuming that the adjustment path to the optimal capital stock[5] follows an ECM, and using the logarithmic approximation $\Delta k_{i,t} = I_{i,t}/K_{i,t-1} - \delta_i$, the dynamic equation for the growth rate of capital becomes (Bean, 1981; Bond and Van Reenen, 2007; Hernando and Martinez-Carrascal, 2003):

$$[1] \quad \frac{\mathrm{I}_{it}}{\mathrm{K}_{i,t-1}} = \alpha_0 \frac{\mathrm{I}_{i,t-1}}{\mathrm{K}_{i,t-2}} + \sum_{i=0}^{n} \alpha_{1i} \Delta \mathrm{y}_{i,t-i} + \alpha_2 (\mathrm{k} - \mathrm{y})_{i,t-2} + \alpha_3 \ln(\mathrm{r})_{t-1} + \alpha_4 \mathbf{X} + d_i + \theta_t + \varepsilon_{it}$$

where i indexes firms, with i=1, 2,…, 13,000, and t indexes years t=1, …,T. The term Δ denotes first differences, I/K the investment rate, y the log of real sales[6], k the log of the real capital stock, r the log of the real user cost of capital[7] and **X** is a vector including our industry relatedness

[4] See Bond and van Reenen (2007) for a review of the microeconometric models used to estimate dynamic investment equations.

[5] As is known this is a solution to the standard firm's profit maximization problem.

[6] Firm sales are deflated using 2-digit production prices drawn from ISTAT.

[7] The real user cost of capital is defined as follows:

$$r_{st} = \frac{p_{kt}}{p_{yst}} \frac{(i_t - \dot{p}_t + \delta)(1 - A \cdot tax_t)}{(1 - tax_t)}$$

variable, its interaction with cash-flow and bank-related variables; we also include additional controls for firm size (small (1-49 employees), medium (50-249 employees) large (more than 250 employees)), industry (low-tech, medium-tech, high-tech, according to the OECD definition) and macro-area (North-West, North-East, Centre, South). Finally, d_i denotes unobserved fixed effects, θ_t time fixed effects, and ε_{it} is the error term with the usual statistical properties. The coefficients α_1 and α_2 indicate the speed of adjustment of capital stock to its equilibrium level which is identified by the term $(k-y)$.

We estimate our investment equations using a *two-step system GMM* estimators (Arellano and Bond, 1991; Blundell and Bond, 1998) which allows us to control for potential bias due to non-observable fixed effects and endogenous dependent variables. This estimation method requires: (i) the absence of second order serial correlation in the first differenced residuals (M2); and (ii) the presence of first order serial correlation in the first differenced residuals (M1). Our estimates satisfy both these conditions on the residuals. We also report the Sargan and Hansen tests for over-identifying restrictions. Both tests show that our instrumentation strategy is valid (Hernando and Martinez-Carrascal, 2003).

3. Results

Table 2 presents the estimation results. Column [1] reports our baseline specification and shows that: investments are positively correlated to lagged growth rate in sales and negatively related to the error correction term and the cash-flow. Thus, we find evidence that, between 2000 and 2007, the current investment rate tends to adjust to its long-run equilibrium level and Italian manufacturing firms are not financially constrained because of the relatively easy access to credit at low interest rates. The estimated coefficient of the real user cost of capital is negative, but not statistically different from zero, as is the district dummy. When looking at bank-related variables, we find that higher operational proximity increases firms' investments, while higher functional distance has no significant effect (although the negative sign of its coefficient is expected).

In Column [2] we extend our basic model by including the index for related variety. Estimates show that the coefficient is positive, but not statistically significant. The most interesting results emerge when we interact cash flow with our proximity variables. Column [3] shows that

where p_k and p_v are investment and output prices, i is the nominal interest rate, p is the inflation rate, δ is the physical depreciation rate, A is the present value of investment allowances per unit of investment, and tax is the statutory corporate tax rate (which includes the fiscal incentives for investment). User costs are calculated for each industry, using the Italian ATECO2007 classification (based on NACE rev. 2).

investments become sensitive to cash flow when both operational proximity and functional distance increase. While the former confirms the possible ambiguous effect of the availability of local branches on local borrowers,[8] the latter clearly shows that credit rationing increases as the organizational proximity between local branches and their headquarters reduces. Column [4] shows that investments become less sensitive to cash flow the more technologically related the LLS, confirming our expectations about the role of industry relatedness in easing firms' financial constraints. However, the results in Column [5] show that the contribution of industry relatedness to the marginal effect of cash flow on investments reverses as functional distance increases. This is a sign that, as banks become more hierarchical and less embedded in the LLS, industry relatedness acts as a barrier to the collection of soft information on inter-firm production and financial linkages.

4. Conclusions

In this paper we studied whether industrial relatedness affects firms' fixed investment behaviour, and whether this relationship is linked also to the geographical and organizational proximity of banks. By estimating different specifications of an ECM dynamic investment equation on an unbalanced panel of 13,000 Italian manufacturing firms for the period 2000-2007, we showed that industrial relatedness boosts investments by lowering their sensitivity to cash flow. We argue that, in technologically related areas, banks tend to reduce credit rationing because of reduced screening and monitoring costs, easier re-allocation of property rights and higher likelihood to establish stable credit relationships with firms. It is interesting that the positive effect of industrial relatedness on investments vanishes as the functional distance between local branches and their headquarters increases. This most likely means that more hierarchical and less embedded banks find it more difficult to collect tacit information on inter-firm production and financial linkages at the local level, and thus reduce credit provision.

[8] Alessandrini *et al.* (2009) find that a higher number of banks for population increases the sensitivity of investments to cash flow, whereas a higher number of banks per square kilometre works in the opposite direction. Other studies provide additional evidence of an amiguous effect of operational proximity on credit rationing (Petersen and Rajan, 2002; Giroud, 2013).

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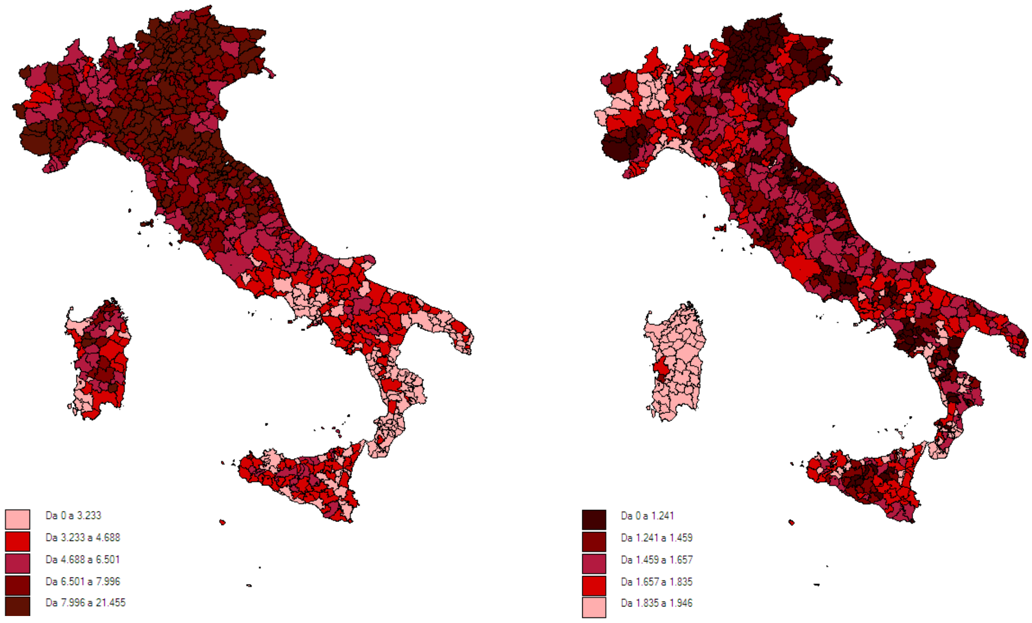
Figure 1 – Operational proximity and functional distance in 2007

(a) Operational proximity (b) Functional distance



Source: Authors' elaborations on Bank of Italy data.

Table 1 – Sample structure

Size	N	%
Small (1-49)	8066	62.0
Medium (50-249)	4421	34.0
Large (250+)	513	3.9
Area (NUTS1)		
North-West	6144	47.3
North-East	3879	29.8
Centre	1875	14.4
South	1102	8.5
Industry (OECD classification)		
Low-tech	4926	37.9
Medium-tech	6273	48.3
High-tech	1801	13.9
Total	13000	100.0

Table 2 – Dynamic investment equation: GMM estimates

ESTIMATION METHOD	TWO- STEP SYSTEM GMM				
	[1]	[2]	[3]	[4]	[5]
$\frac{I_{i,t-1}}{K_{i,t-2}}$	0.014	0.057	0.056	0.209	0.209
	[0.136]	[0.142]	[0.143]	[0.159]	[0.153]
$\Delta y_{i,t}$	0.047	0.045	0.046	0.045	0.043
	[0.046]	[0.046]	[0.048]	[0.043]	[0.042]
$\Delta y_{i,t-1}$	0.146***	0.124***	0.133**	0.094*	0.088**
	[0.047]	[0.046]	[0.056]	[0.052]	[0.042]
$(k-y)_{i,t-2}$	-0.144***	-0.122***	-0.131**	-0.092*	-0.087**
	[0.046]	[0.045]	[0.055]	[0.051]	[0.041]
$\ln(r)_{i,t-1}$	-0.062	-0.039	-0.079	-0.222*	-0.234*
	[0.171]	[0.198]	[0.173]	[0.133]	[0.137]
$\frac{CF_{i,t-1}}{K_{i,t-2}}$	-0.015**	-0.015**	0.039	0.061	0.047**
	[0.007]	[0.007]	[0.024]	[0.035]	[0.019]
$District_s$	-0.093	-0.105	-0.088	-0.011	-0.010
	[0.067]	[0.077]	[0.071]	[0.007]	[0.007]
$OP_{s,t}$	1.805**	1.994*	1.213	-0.009	-0.015
	[0.858]	[1.068]	[1.338]	[0.010]	[0.010]
$FD_{s,t}$	-0.821	-1.354	-0.753	-0.014	-0.048**
	[0.697]	[1.095]	[0.655]	[0.011]	[0.019]
$\frac{CF_{i,t-1}}{K_{i,t-2}}$ x $OP_{s,t}$			0.085**		
			[0.033]		
$\frac{CF_{i,t-1}}{K_{i,t-2}}$ x $FD_{s,t}$			0.408**		
			[0.167]		
$RV_{s,1991}$		0.300		-0.007	-0.015
		[0.191]		[0.005]	[0.018]
$\frac{CF_{i,t-1}}{K_{i,t-2}} \times RV_{s,1991}$				-0.011**	
				[0.004]	
$\frac{CF_{i,t-1}}{K_{i,t-2}} \times FD_{s,t} \times RV_{s,1991}$					0.068**
					[0.028]
Time dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Size dummies	Yes	Yes	Yes	Yes	Yes
Geographic dummies	Yes	Yes	Yes	Yes	Yes
N. obs.	71,231	71,231	71,231	71,231	71,231
N. firms	13,000	13,000	13,000	13,000	13,000
M_1 (p-value)	0.000	0.000	0.000	0.000	0.000
M_2 (p-value)	0.736	0.491	0.500	0.071	0.064
Sargan test (p-value)	0.908	0.882	0.897	0.260	0.416
Hansen test (p-value)	0.726	0.713	0.790	0.379	0.343
N. instruments	48	49	50	52	53

*** significant at 1%; ** significant at 5%; * significant at 10%; standard errors are in parentheses and are clustered at LLS level.