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Transport endowment, knowledge spillovers and firm performance in emerging economies

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Abstract This work explores the link between firm performance in emerging economies and transport infrastructure endowment, as a key element of the entrepreneurial ecosystem. We ground on the idea that transport infrastructures, by enabling connectivity, interactions and the exchange of knowledge and ideas, have the potential to enhance commercial opportunity recognition, technological development and, thus, firm economic performance. We also emphasize the crucial role of logistics system performance in providing better linkages between suppliers, firms and customers. The empirical analysis is focused on emerging economies whose infrastructure endowment is lower than those of developed ones; thus, its improvement is likely to be associated with better performance of their firms and economies. The results suggest that part of country-level differences in firm's labour productivity is explained by transport endowment. Particularly, transport networks, such as roads and railways, and the logistics system and services show strong and positive relationships with productivity, while transport nodes, such as airports and ports, show little or no association. This might occur because networks spread knowledge spillovers in a more capillary way compared to nodes. Overall, the empirical results suggest that policy-makers in emerging economies can sustain the economic performance of firms, with beneficial effects on the economic system, by improving their transport endowment.

Plain English Summary Firms are part of national ecosystems whose attributes may influence their performance and, therefore, the economic growth of a country. In this paper, we focus on transport infrastructure endowment. We distinguish between transport networks and transport nodes, and we consider the logistic system and services. Our research questions are tested on a sample of firms in emerging economies. In so doing, we combine micro-data on firms from East Europe and Central Asia with macro-data on transport endowment. We show that more developed transport systems are positively associated with better economic performance of firms. Particularly, the beneficial effect of transport networks is found to be more prominent, possibly because more developed transport networks are associated with increased opportunities for knowledge exchange between firms. Also, the logistics system is linked to better firm performance by reducing time and distance constraints and providing better linkages along the supply chain.

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1 Introduction

Firms are widely considered the main driver of a country's economic performance (e.g. Birch, 1981; Audretsch and Thurik, 2000; Reynolds et al., 2001; Audretsch and Fritsch, 2002). This literature has its origins in Schumpeter's (1934) theory of endogenous growth, which argues that, to promote economic growth, it is essential to understand the determinants of entrepreneurial activity and to encourage it. The development of a country starts from the bottom, and "development-from-below" relies significantly on local resources, enterprises and actors (Helmsing, 2005).

It is also widely recognized that differences in performance between firms are due to their internal resources and to their behaviour (Jensen and McGuckjn, 1997; Bernard et al., 2012; Coad et al., 2018). However, firms do not exist in isolation; they are part of an entrepreneurial ecosystem (Stam, 2015; Stam and Spigel, 2018; Stam and Van de Ven, 2021), within a specific national context, whose elements may influence their creation, performance and even survival (Acs et al., 2014, 2016, 2018; Alvedalen and Boschma, 2017; Brown and Mason, 2017; Ndiaye et al., 2018). Therefore, for an in-depth understanding of firm performance, country-level factors should be considered together with firm-level factors (Commander et al., 2008; Commander and Svejnar, 2011; Goldszmidt et al., 2011).

In this paper, we investigate the relationship between transport infrastructure endowment at the country-level with firm performance in emerging economies. Grounding on the knowledge spillover theory of entrepreneurship (KSTE) introduced by Audretsch (1995), we argue that transport infrastructures, by enabling connectivity, interactions and the exchange of knowledge and ideas, facilitate the access to entrepreneurial opportunities and capabilities to implement those opportunities. It follows that well-developed transport infrastructures have the potential to promote the economic performance of firms (Audretsch and Lehmann, 2005; Ghio et al., 2015; Audretsch et al., 2015).

The role of transport infrastructures in aggregate economic growth is proved to be relevant (Fromm, 1965; Aschauer, 1989; Calderón and Servén, 2004; Button, 2010; Bottasso and Conti, 2010; Calderón et al., 2015; Ferrari et al., 2018), especially in the context of emerging economies where the infrastructure endowment is lower compared to more developed economies, so its improvement is likely to have a greater impact on their economy (Baum-Snow et al., 2017; EBRD, 2018; Li and Li, 2013). Moreover, the role of physical infrastructures as an element of the systemic nature of the entrepreneurial ecosystem (Audretsch et al., 2015; Stam, 2015; Stam and Spigel, 2018; Stam and Van de Ven, 2021) and its national dimension (Acs et al., 2014; Urbano, et al., 2019) is recognized by scholars. Despite this, to the best of our knowledge, studies that investigate the linkage between the heterogeneity of firm performance in emerging economies and transport infrastructure endowment, as a key element of the entrepreneurial ecosystem, are absent. In this paper, we aim to fill this gap. For this purpose, we consider transport networks, such as roads and railways, and transport nodes, such as airports and ports. Moreover, we consider the logistics system and services, which has been largely overlooked by the literature on entrepreneurship.

Due to the coexistence in the analysis of factors that, at different levels, might be related to firm performance, we examine them in an integrated framework through the multilevel approach. This approach allows to define a two-level hierarchical structure, where firms are nested in countries and, at the same time, to separate the effect of firm-level factors from the effect of transport infrastructures and logistics on the heterogeneity of firm performance.

For the purpose of this research, we combine firm-level data on 32 countries in Eastern Europe and Central Asia from the fifth round of the Business Environment and Enterprise Performance Survey (BEEPS V) conducted in 2012–2016, by the European Bank for Reconstruction and Development (EBRD) and the World Bank (WB), with country-level data on transport infrastructures and logistics collected from institutional data sources.

The rest of the paper is structured as follows. Section 2 discusses the theoretical background and develops the research hypotheses. Section 3 outlines the description of the data and the construction of the variables. Section 4 presents the methodology used to investigate the determinants of firm performance. Section 5 shows and discusses the empirical results. In Section 6, the robustness of the previous analysis is investigated. Finally, concluding remarks are summarized in Section 7.

2 Theoretical background and hypothesis development

2.1 Linking transport infrastructures and logistics to firm performance in emerging economies

The individual entrepreneur is not the sole locus of value creation. The entrepreneurial activity needs to be placed in a broader context which consists of all the elements that are required to sustain productive entrepreneurship, the so-called entrepreneurial ecosystem (Stam, 2015; Stam and Spigel, 2018; Stam and van de Ven, 2021). By commercializing innovations, entrepreneurs act as agents that trigger the mechanism of transferring knowledge advances into economic growth. Even where entrepreneurial initiative is present, this process of transmission can be either hindered or facilitated by the environment in which the businesses operate (Acs et al., 2018), which provides resources that agents can mobilize to exploit entrepreneurial opportunities (Acs et al., 2014; Alvedalen and Boschma, 2017; Brown and Mason, 2017). Indeed, the entrepreneurial context can influence how aggressively the firm will pursue growth and with what outcomes (Acs et al., 2016).

The literature on entrepreneurship unanimously recognized that knowledge is key in ecosystems (Acs et al., 2013; Cantner et al., 2021; Stam and van de Ven, 2021). In this regard, the KSTE sustains that entrepreneurial behaviour is a response to profitable opportunities from knowledge spillovers. An entrepreneurial context that is rich in knowledge encourages the development of new technologies, promotes the entrepreneurial activity and enhances the economic performance of firms (Audretsch and Lehmann 2005).

The spillover of knowledge from its source is not automatic but is hampered by the *knowledge filter*, a term that refers to the barriers that prevent knowledge from spilling over for innovation and commercialization (Acs et al., 2013). In this regard, transport infrastructure development improves connectivity and interactions, thus facilitating the exchange of knowledge and ideas that could fuel entrepreneurial ventures (Audretsch and Lehmann, 2005; Ghio et al., 2015; Audretsch et al., 2015). From this perspective, the mobility of economic agents serves as the conduit of knowledge spillovers (Audretsch and Keilbach, 2005). Locations with well-developed transport infrastructures, by attracting new firm establishment (Holl, 2004a; Arauzo-Carod and Viladecans-Marsal, 2009), promote agglomeration mechanisms that, in turn, enhance knowledge exchange and diffusion between firms — because geographic proximity is important for the transmission of knowledge spillovers (Audretsch, 1998) — labour market pooling and input sharing. Moreover, transport infrastructures can have a positive impact on firm-level productivity by reducing transport costs and facilitating the movement of goods and the labour force (Holl, 2016).

From the discussion above emerges that transport infrastructure endowment, among other elements of the entrepreneurial context, by enabling knowledge spillovers, has the potential to stimulate firm-level performance. Several studies show that transport infrastructures play a key role in economic processes, but, to the best of our knowledge, there is a lack of studies that place attention on transport infrastructures as a crucial element in the entrepreneurial ecosystem (see Wurth et al., 2022), with a few exceptions (Audretsch et al., 2015). Therefore, this paper contributes to the research on entrepreneurship and small business economics by analysing the economic performance of firms to assess whether the reason why some firms outperform others can be also traced to the unobserved heterogeneity due to country-level differences in the transport infrastructure endowment and, thus, in the transmission of knowledge spillovers and in the ability to foster entrepreneurial activity.

The concept of entrepreneurial ecosystem (Cao and Shi, 2021) and KSTE (Iftikhar et al., 2020) in the context of emerging economies and developing countries recently starts receiving attention. Firms in emerging economies are typically small and young and offer significant benefits in terms of job creation, innovation and, ultimately, economic growth. Among the others, Decker et al. (2015) demonstrate that the expansion of young firms, but also their creation, can be a significant driver of growth. In emerging economies, the endowment of transport infrastructures is lower and shows different bottlenecks compared to more developed economies. Its improvement, by fostering knowledge spillovers among firms, is expected to have a positive relationship with their economic performance and, thus, on the economy as a whole.

In this context, the difference between connectivity and accessibility needs to be considered. While connectivity is an attribute of a network and measures the minimum number of links needed to reach all nodes from all other nodes, accessibility is an attribute of a node and measures the minimum number of links needed to reach all or certain nodes from a specific node (ESCAP, 2007). We suggest that a clear distinction should be made in terms of networks and nodes, which can be defined as "connectivity" and "accessibility" characteristics of a transportation system. Therefore, we develop the research hypotheses on the role of transport infrastructures in firm performance by distinguishing transport infrastructures by their attributes, as *networks*, when considering roads and railways, and as *nodes*, when we refer to ports and airports. Finally, we also consider the role of logistic system and services in supporting firm performance

2.2 Empirical evidence and hypothesis development

The first paper to examine the link between infrastructures and entrepreneurship is that of Audretsch et al. (2015), who posit that, by enhancing connectivity and linkages that facilitate entrepreneurial opportunity recognition, infrastructures can promote the creation of start-ups. Audretsch et al. (2015) show that railways do promote the start-up of new firms in German regions, while highways yield limited or no impact on entrepreneurial activity because Germany has a very dense motorway network, extensively connecting even remote areas.

In the specific context of high-speed rail (HSR), Chen and Hall (2011) show that HSR reinforces the transition of local economies to knowledge economies, and Komikado et al. (2021) find that HSR development promotes knowledge productivity enhancements at an international scale. Some studies also point out that the impact of HSR on knowledge sharing is largely due to its uniqueness in offering inter-regional passenger transport (Inoue et al., 2017; Tamura, 2017).

Agrawal et al. (2017) and Bottasso et al. (2022) place their attention to road networks. Agrawal et al. (2017) explore the effect of highways on regional innovation in the USA and report evidence that an increase in regional highway stock leads to an increase in regional patenting. This happens because roads have a strong knowledge diffusion effect because facilitate the local knowledge flows and increase the likelihood that innovators access knowledge inputs even from more distant neighbours. Particularly, highways have a larger impact on innovation in low-density regions, where inventors are likely to be more spread out. Bergantino et al. (2013) investigate the R&D efficiency of Italian regions and find that disparities in rail and road network development reflect on regional performance. Also, Bottasso et al. (2022) focus on the innovative performance of Italian regions and show that highway stock has an innovation-enhancing effect because it fosters collaborations among inventors by reducing travel costs and it increases the centrality in the regional innovation network. Particularly, highways are found to increase innovation by spreading knowledge diffusion between regions and not only within regions.

The empirical evidence on emerging economies is mostly on China. Wang et al. (2018) investigate the relationship between city-level road density and firm-level innovation, showing that increasing road density spurs innovation by expanding market size and promoting knowledge spillovers. At a more aggregate level, Zhang et al. (2020) show that HSR increases regional proximity and, thus, stimulates information flows and corporate innovation. Moreover, Yang et al. (2021) show that HSR not only accelerates innovation growth at prefecture-level but also promotes innovation convergence. Consistently, Komikado et al. (2021) explain that the existence of HSR stations, a proxy of accessibility, is positively associated with knowledge productivity, and Tang et al. (2022) show that knowledge spillovers are important manifestations through which HSR promotes regional innovation and total factor productivity.

On this basis, we argue that the development of transport networks improves connectivity, reduces the cost of face-to-face communication, fosters collaborations and knowledge spillovers and, ultimately, can enhance the performance of firms in emerging economies. Therefore, we put forth the following research hypothesis:

> Hypothesis 1: Transport networks are positively related to the performance of firms in emerging economies.

Zhang and Graham (2020) develop a conceptual framework showing that the impact of air transport on the economy mostly arises through its supply chain effects and spillover effects. The supply chain effects are related to the employment and the economic activity that air transport supports both directly and indirectly. The spillover effects are related to the substantial reduction of long-distance constraints that increases accessibility and enables enhanced economic interactions, thereby creating locational advantages. Bilotkach (2015) shows that air transport has a positive impact on key indicators of regional economic development in the USA, such as the employment, the number of business establishments and the average wage. Along the same lines are the findings of Bergantino et al. (2013), according to which air accessibility plays a positive role in increasing regional R&D output in Italy. The positive linkage of airport activities to regional economies more recently emerges also for New Zealand (Fu et al., 2021). Finally, evidence from Chinese cities shows that airports have a positive and significant effect on economic development, not limited to the economy of the city served, but extended to other connected cities (Chen et al., 2021).

Bottasso et al. (2014) explore the impact of port activities on local development by assessing the direct and indirect (i.e. spillover) effects of seaports in regions located in thirteen European countries. Their results reveal that ports tend to increase GDP in the area where they are located, but there are significant positive spillover effects on the GDP of nearby regions, suggesting that the economic relevance of ports spreads beyond the port regions. Additionally, the presence of a port is found to be an attractive factor for the location decisions of foreign direct investments (Belderbos and Carree, 2002; Deichmann et al., 2005).

The discussion above induces us to conjecture that transport nodes, by increasing the accessibility and the economic interactions, improve the performance of firms in emerging economies. Thus, we formulate the following research hypothesis:

> Hypothesis 2: Transport nodes are positively related to the performance of firms in emerging economies.

Overall, well-developed transport infrastructures are expected to improve a country's accessibility, which is crucial for firms also because a substantial part of their activities requires moving inputs and outputs. The organization of modern economies is built upon an efficient transport system, and an increasing role is played by the logistics sector in overcoming the constraints of time and distance in the supply chains.

Logistics is defined as the movement, handling and storage of goods from supply, through production and distribution to customers (Holl, 2006). In an increasingly globalized environment, logistics also become one of the main engines of competitiveness and economic development (Jiang et al., 2016). As demonstrated by the literature, there is a bidirectional link between logistics performance and economic development (Arvis et al., 2007; Lean et al., 2014), but this link has been less investigated at micro-level.

Considering all the above, we argue that a more efficient logistics system with more qualitative connectivity reduces time and distance constraints and provides better linkages between suppliers, firms and customers, thus supporting the economic performance of firms. Therefore, we formulate the following research hypothesis:

> Hypothesis 3: The performance of the logistics system is positively related to the performance of firms in emerging economies.

Summing up, this paper is among the few in the literature that comprehensively explores the role of transport infrastructure endowment — transport networks, transport nodes and logistics system — in the performance of firms in emerging economies.

2.3 Measures of transport infrastructures

The empirical literature declines transport infrastructures differently based on measures used, which may influence the evidence provided.

The availability of data for transport is usually one of the key constraints to study the effect of the transport system on the creation, performance and survival of firms. It becomes more difficult for emerging economies, where previous analyses rely more on considering firms' perceptions of transportation constraints (see, among others, Dollar et al., 2005; Carlin et al., 2006; Aterido et al.,

2011) that may lead to methodological problems (Dethier et al., 2011). As a result, studies either use a crude measure of transport or have better measures of transport for fewer time periods (Melo et al., 2010).

Various studies use general measures for transport. For instance, Coughlin and Segev (2000) employ a dummy variable to account for the presence of interstate highways, which appears to be positively associated with the number of new firms in US counties. Fotopoulos and Spence (1999) consider the amount of per capita public investment in the public infrastructure provision, having a positive impact on new plant openings in Greece. Holl (2004a, 2004b, 2004c) uses distance to the motorway network to measure the availability of this transport infrastructure. She finds that improvements in the distance to the nearest motorway have an important role in the formation of new establishments in Portuguese and Spanish municipalities, where plant openings are higher in municipalities that have access to a motorway within 10 km and fall with increasing distance.

This issue appears relevant to be discussed, given that the literature provides different results related to entrepreneurship, innovation and, more generally, to firm economic performance depending also on how transport infrastructures are defined and measured in empirical analysis. Indeed, Audretsch et al. (2015) posit that research needs to take infrastructure more seriously by creating new measures of more specific types of infrastructures, pointing out another fundamental question, such as the role of infrastructure quality. The types of infrastructures can be either considered as measures of accessibility in the transport network (see Audretsch et al., 2015; Yang et al., 2021) or as connectivity measures when related to transport nodes, considering flows or number of destinations (see Bilotkach, 2015; Bottasso et al., 2014).

In Table 1, we provide a summary of the main empirical works that investigate the role of transport infrastructures from the KSTE perspective, namely, in promoting knowledge transmission between firms and, at a more aggregate level, between regions or countries. This table offers an overview of how transport measures are defined and how they contribute to the empirical evidence.

3 Data and variables

To test the hypotheses on the relationship between country-level transport endowment and firm performance in emerging economies, we combine firm-level data on 32 countries from East Europe and Central Asia, drawn by the fifth round of BEEPS V conducted in the period 2012–2016[1] by the EBRD and the WB, with country-level data, collected from institutional data sources. Based on face-to-face interviews with firms' owners and managers, BEEPS V provides detailed performance information on about 16,000 firms from the main manufacturing and service sectors.

To analyse firm performance, we rely on the log-linear Cobb–Douglas production function with constant return to scale, where the dependent variable is the natural logarithm of firm productivity. Given the information gathered from BEEPS V, we define firm productivity as sales (in US dollars) per employee, the so-called labour productivity.[2] Moreover, we proxy the variable capital with the investments (in machinery, vehicles, equipment, land or buildings) per employee in US dollars, expressed in natural logarithm.[3]

We augment the Cobb–Douglas production function by including a set of firm-level explanatory variables to control for internal factors that might influence the heterogeneity in performance among firms. Many empirical works investigate the relationship between firms' growth and age (e.g. Coad et al., 2013). As age is closely related to competitive processes, as innovation activities (Mateut, 2018), the relationships with firm performance are expected to be positive[4] (Jensen and McGuckjn, 1997). On this basis, we define the binary variable start-up equal to 1 if the firm starts

[1] In the EBDR survey, information on firms refers to the fiscal year previous to the period in which the survey was carried out (about 9% of observations refer to fiscal years after 2011).

[2] The labour productivity is a partial measure of productivity. However, this approach has been adopted by some relevant papers exploring firm productivity, such as Baumann and Kritikos (2016), Audretsch and Belitski (2020) and Audretsch et al. (2020).

[3] Due to the lack of information in the data on the cost of capital for the whole sample of firms, we adopt the approach of Audretsch et al. (2020) and Baumann and Kritikos (2016); thus, we proxy capital by investments.

[4] Sometimes controversial, instead, is the relationship with age, since firms might incur in productivity losses as they become older (Burki and Terrell, 1998).

Table 1 Summary of empirical evidence, measures and definitions of transport infrastructures in the knowledge spillover theory literature

Authors	Transport variables	Model	Time period	Geography	Results	Knowledgespillover effects
Bergantino et al. (2013)	Density (and extension) of railway and road network. Air accessibility as the total number of passengers	Two-step DEA	1995–2012	20 Italian regions	Accessibility and transport network infrastructure improve R&D efficiency by facilitating connections and knowledge transfer among R&D producers	Yes (railway and road network) Yes (air accessibility)
Bottasso et al. (2014)	Port total throughput Accessibility index at inter-regional level Motorways in km of network	Spatial Durbin model (SDM)	1998–2009	Regions of 13 European countries	Spillover effects of port throughput exist locally. Globally, knowledge spillovers tend to directly affect neighbouring units	Yes (port activity)
Audretsch et al. (2015)	Number of motorway interchanges Number of long-distance train stations	OLS with clustered standard errors	2000–2004	German municipalities	Railway infrastructures conduce to new firm start-ups, mainly in technology-oriented services, consumer-related services and retail trade, not in high-technology or low-technology manufacturing No impact of highway infrastructures	Yes (railway accessibility) No (highway accessibility)
Agrawal et al. (2017)	Instrumental variables: total number of kilometres of highway in 1947 Major railroad lines in km from about 1898	OLS and IV	1983–1988	268 Metropolitan Statistical Areas (MSAs) in USA	10% increase in a region's stock of highways causes a 1.7% increase in regional patenting over a 5-year period Positive impact of roads on regional innovation at the more disaggregated MSA-technology-class level. Positive impact of railways on innovation activities in the 1980s	Yes (highways and railroads network)

Table 1 (continued)

Authors	Transport variables	Model	Time period	Geography	Results	Knowledgespillover effects
Wang et al. (2018)	Road area density: the share of road area in the city's total administrative area	OLS and IV	1998–2007	All manufacturing enterprises in China	A 10% increase in road density would increase a firm's number of patents by 0.71%, corporate R&D investment by 1.42% and the probability to have patents would increase by 0.39%	Yes (road connectivity)
Bottasso et al. (2022)	Total number of kilometres of motorways Major roman roads 117 AD as IV	Social network analysis (SNA) Gravity model	1978–2015	Italian regions	Denser highway networks favour collaborations among inventors. Node centrality within a collaboration network exerts a positive impact on regional innovation	Yes (highway network)
Yang et al. (2021)	HSR dummy variable Number of HSR stations Number of HSR lines Road passenger volume per 10,000 people Air passenger traffic	Cobb–Douglas production function	2003–2013	285 cities above prefecture-level in China	HSR promote innovation with an effect value of 14.73% in China regions. HSR promotes innovation convergence among cities Significant and positive effect of road and airlines status	Yes (HRS accessibility and connectivity measures, road and airport flows)
Miwa et al (2022)	HSR dummy Expressway dummy ED as regional accessibility for HRS and expressways	Difference-in-differences (DID) model, propensity score matching and IV	1976–2016	1741 municipalities in Japan	HSR on regional innovation in small towns and villages is larger than that in large cities. Expressways do not stimulate regional innovation	Yes (HRS accessibility) No (expressway accessibility)
Tang et al. (2022)	Dummy variable whether high-speed railway opens in a city	Time-varying difference-in-differences (DID) model Super SBM-DEA model	2006–2016	China cities	Knowledge spillovers are important manifestations through which HSR promotes regional innovation. HSR can significantly improve the level of total factor productivity and human capital. Urban form mediates the impact of HSR on regional innovation significantly	Yes (HRS accessibility)

operations in the last 5 years, 0 otherwise. Exporting firms are typically considered more productive than non-exporting firms (Bernard et al., 1995) with significant implications for international strategic decisions (Pongelli et al., 2016). Also, foreign participation in firms' ownership seems to positively affect performance, especially in emerging economies (Asiedu and Esfahani, 2001; Douma et al., 2006; Gurbuz and Aybars, 2010; Hintošová and Kubíkovál, 2016). Thus, we include in the analysis the abovementioned aspects by introducing the dummy variables: exporter, equal to 1 if the firm exports some of its outputs, 0 otherwise; and foreign, equal to 1 if 1% of assets or more are owned by private foreign individuals, companies or organizations, 0 otherwise. In a globalized and competitive marketplace, the endowment of a skilled workforce can explain why some firms outperform others (Barney et al., 2001; Acedo et al., 2006). The literature provides evidence of the positive association between human capital and overall firm performance (Crook et al. 2011), especially for small firms (Lepak and Snell, 2002; Coder et al., 2017). Therefore, we define the variable qualification as the share of permanent full-time employees holding a university degree. Finally, to control for sectoral patterns, we define a set of industry dummies, named SEC.[5] Due to missing values, we end up with 10,954 firms with complete observations.

To address our research hypotheses, firm-level productivity is associated with different measures of country-level transport endowment. Specifically, to test Hypothesis 1 on transport networks, we define two variables: road, the total roads in km per square km, including expressways and paved and unpaved urban roads, and rail, the total railways in km per square km, including public and non-public railways. To test Hypothesis 2 on transport nodes, we define the two variables: airport, the number of airports paved runways per 1000 square km, and port, the number of total ports.[6] Finally, to test Hypothesis 3, we employ the logistic performance index (LPI),[7] providing an assessment of the managerial and physical effectiveness of a country's logistics. Overall, this measure indicates the relative ease and efficiency with which products can be moved and how the logistics system works as trade facilitator.

The sample of emerging economies considered consists of countries belonging to different income groups with disparities in terms of development. Therefore, we introduce as control variable gap, the ratio between the GDP per capita (expressed in PPP constant 2011 international USD) of the most developed economy in the sample and the observed country (Y^*/Y, where Y^* is the most developed country in the sample and Y the observed country), to account for different levels of development across countries that can affect firm performance.

Country-level data are collected from the European Commission, the World Bank and the Central Intelligence Agency for the reference year 2011. A table with a summary definition of variables and their sources is included in the Appendix (Tables 8, 9, 10, 11 and 12). General descriptive statistics are reported in Table 2.

Descriptive statistics show high heterogeneity levels. The mean of labour productivity is about 121,000 US dollars per employee displaying significant variation among countries. Around 15% of the firms in the sample are start-ups representing the age class from 0 to 5 years, while the average age of firms is around 15 years, and 86% are small and medium enterprises, suggesting that firms in emerging economies are quite young and relatively small. Overall, firms with the participation of foreign capital represent 7% of the sample, while only 22% of firms occur in export activities, with considerable variation both across firms and countries. Lastly, the share of permanent employees holding a university degree reported by firms is around 33% of the total permanent full-time employees. In

[5] Sectors are grouped in seven categories as follows: (i) high technology; (ii) medium-high technology; (iii) medium-low technology; (iv) low technology; (v) construction, retail and distribution; (vi) knowledge intensive business services; and (vii) other business service. The grouping criteria of industries follow the OECD (2011) and Eurostat classifications.

[6] This variable includes the major seaports, riverports, container ports, oil and LNG terminals.

[7] The LPI is a summary indicator of logistics sector performance, combining data on six core performance components into a single aggregate measure: *customs, infrastructure, international shipment, logistics quality and competence, tracking and tracing timeliness*. LPI ranges from 1 *(worst performance)* to 5 *(best performance)*. Usually, a value lower than 3 reflects an array of problems within a country's freight distribution system, causing undue delays and additional costs. Data are collected biannually, the mean of the overall scores for the years 2010 and 2012 is considered.

the Appendix, we provide additional descriptive statistics regarding the between and within variability of firm-level variables due to country clusters (Tables 8, 9, 10, 11 and 12). There is a considerable variation in the mean of firms' labour productivity among countries, from 22,000 US dollars per employee for Ukraine up to 498,000 US dollars for Cyprus. Figure 1 shows labour productivity for each country in the sample.

Additional descriptive statistics of transport infrastructures and logistics and control variables are reported in Table 3.

The density of roads and rails shows considerable differences between countries. The average density is 0.63 and 0.03, respectively. The less endowed country is Mongolia for both kinds of infrastructures, while the most endowed countries are Hungary and Czech Republic. The number of airports paved per 1000 square km shows also high variation, where Mongolia is the last country with a density value of 0.01, while Czech Republic and Cyprus have the highest airport density of the group, with a value of 1.62. As far as ports are concerned, Turkey is the country with the highest number of ports. Clearly, the presence of port facilities is due to the geographical position of a country. Finally, the average score of LPI is 2.82. Poland has the best logistic performance of the sample countries, scoring 3.43 points, whereas Mongolia has the worst scoring, only 2.25 points. The correlation matrix among country-level variables is reported in the Appendix (Tables 8, 9, 10, 11 and 12).

Table 2 Descriptive statistics

Variable	*Obs.*	*Mean*	*St. dev.*	*Min*	*Max*
Firm-level variables					
Labour productivity	10,954	121.49	1021.97	0	73,700.00
Capital	10,954	5.97	266.27	0	27,200.00
Start-up	10,954	0.15	0.36	0	1
Exporter	10,954	0.22	0.42	0	1
Qualification	10,954	32.67	30.81	0	100
Foreign	10,954	0.07	0.26	0	1
Country-level variables					
Gap	32	3.26	3.14	1	15.01
Road	32	0.63	0.59	0.03	2.18
Rail	31	0.03	0.03	0	0.12
Airport	32	0.47	0.40	0.03	1.62
Port	32	3.19	2.87	0	11
LPI	31	2.82	0.31	2.25	3.43

No official data available for Cyprus on rail infrastructure and for Kazakhstan on LPI. Labour productivity and Capital are expressed in 000 USD/employee

4 Firm performance nested in countries: the multilevel modelling approach

The hierarchical structure of the micro-level data — firms (level 1) nested in countries (level 2) — implies a violation of the assumption of independence among observations within the second-level units. To deal with this issue, we refer to the class of multilevel models enabling us to explicitly model the hierarchical structure of the data and the unobserved heterogeneity (Raudenbush and Bryk, 2002; Goldstein, 2011; Rabe-Hesketh and Skrondal, 2012).

First, the level-1 model corresponds to the following linear regression model:

$$\begin{aligned}&LABOUR\ PRODUCTIVITY_{ij}\\&=\beta_{0j}+\beta_{1j}CAPITAL_{ij}+\beta_{2j}STARTUP_{ij}+\beta_{3j}EXPORTER_{ij}\\&+\beta_{4j}QUALIFICATION_{ij}+\beta_{5j}FOREIGN_{ij}+\textstyle\sum_{k=1}\delta_{0k}SEC_{ik}+e_{ij}\end{aligned}\tag{1}$$

where i indexes the firm and j the country, β_{0j} is the standard intercept, β_{1j} to β_{5j} are the standard slope coefficients, and e_{ij} is the standard error term.

Second, the level-2 model assumes that the intercept (β_{0j}) and the coefficients (β_{1j} to β_{5j}) are nested in countries:

$$\begin{aligned}&\beta_{0j}=\gamma_{00}+\gamma_{01}GAP_j+\gamma_{02}ROADS_j+\gamma_{03}RAILS_j\\&+\gamma_{04}AIRPORTS_j+\gamma_{05}PORTS_j+\gamma_{06}LPI_j+u_{0j}\\&\beta_{1j}=\gamma_{10}+u_{1j}\\&\beta_{2j}=\gamma_{20}+u_{2j}\\&\beta_{3j}=\gamma_{30}+u_{3j}\\&\beta_{4j}=\gamma_{40}+u_{4j}\\&\beta_{5j}=\gamma_{50}+u_{5j}\end{aligned}\tag{2}$$

where γ_{00} is the estimated mean of sales across countries and the coefficients γ_{01} to γ_{06} are the fixed effects of each country-level predictor, while the coefficients γ_{10} to γ_{50} are the estimated mean of the firm-level slopes across countries, and u_{0j} to u_{5j} are the random-specific country effects that represent also the level-2 error term. The random effects can be considered as the effect of omitted country-specific variables, causing performance heterogeneity among firms within the same country (Rabe-Hesketh and Skrondal, 2012).

Fig. 1 Mean of firms' labour productivity by country clusters (sales in US dollars per employee). Source: Authors' computation based on BEEPS V data. Firm-level data are collected over the period 2012–2016 and refer to the fiscal year previous to the period in which the survey was carried out

By combining the level-1 model and level-2 model, the reduced form of the random-coefficients model can be expressed as

$$\mathit{LABOUR\ PRODUCTIVITY}_{ij} = \gamma_{00} + \sum\nolimits_{m=1}^{M} \gamma_{0m} Z_{mj} + \sum\nolimits_{n=1}^{N} \gamma_n X_{nj} + \sum\nolimits_{n=0}^{N} u_{nj} + \sum\nolimits_{k=1} \delta_{0k} \mathit{SEC}_{ik} + e_{ij} \tag{3}$$

where n is the number of firm-level predictors (N=5), m is the number of country-level predictors (M=6), X_{nj} and Z_{mj} are, respectively, the predictor vectors, and u_{nj} is the vector of random effects. The random effects $\sum_{n=0}^{N} u_{nj}$ represent all the factors at country-level that are not observed and are not explained by firm-level characteristics, thus providing useful information on cross-country differences.

We carry out the multilevel analysis by going through different steps. First, to detect the existence of the hierarchical structure in the data, we consider the *variance-components model* that includes only the intercept among covariates. Second, by adding level-1 variables, we estimate a *random-intercept model*, where only the intercept is allowed to vary across countries. Third, we consider the *random-coefficient model*, with only level-1 variables, allowing also the estimated coefficients of level-1 variables to vary across countries. Finally, we extend the latter model by introducing level-2 predictors to assess the effect of transport infrastructures and logistic services in reducing level-2 variability, thus explaining intra-country firm performance differences not already explained by firm-level characteristics.

Further, the Likelihood ratio test, which assumes under the null hypothesis that random effects are jointly equal to zero, is performed after each regression to test the goodness of our model decision. We also test for firm performance variability across countries by calculating the intra-class correlation (ICC) coefficients (ρ) across estimated models, which express the ratio between country-level variance and the total variance, showing the proportion of total variance in firm performance that is accounted for by countries. The intra-class correlation quantifies the degree to which firms with a fixed degree of relatedness resemble each other in terms of a quantitative trait — operating within the same country.

Table 3 Descriptive statistics of country-level variables by country for the year 2011.

	Gap	Road	Rail	Airport	Port	LPI
Albania	3.25	0.12	0.015	0.14	4	2.62
Armenia	4.73	0.26	0.028	0.37	0	2.54
Azerbaijan	2.11	0.22	0.024	0.43	1	2.56
Belarus	1.93	0.48	0.026	0.31	2	2.61
Bosnia Herzegovina	3.35	0.34	0.020	0.47	5	2.82
Bulgaria	2.12	0.2	0.036	0.61	2	3.02
Croatia	1.6	0.56	0.048	1.22	6	2.97
Cyprus	1	1.38	.	1.62	5	3.19
Czech Republic	1.15	1.69	0.120	1.62	3	3.32
Estonia	1.35	1.32	0.018	0.40	6	3.01
FYR Macedonia	2.86	0.54	0.027	0.39	0	2.69
Georgia	4.54	0.27	0.022	0.32	2	2.89
Greece	1.27	0.89	0.019	0.58	7	3.08
Hungary	1.45	2.18	0.085	0.44	5	2.76
Kazakhstan	1.56	0.04	0.005	0.04	5	.
Kosovo	4.06	0.18	0.031	0.55	0	2.49
Kyrgyzstan	11.36	0.17	0.002	0.14	1	3.01
Latvia	1.68	0.92	0.029	0.65	2	3.04
Lithuania	1.45	1.29	0.027	0.93	3	2.67
Moldova	7.94	0.28	0.034	0.21	0	2.45
Mongolia	3.74	0.03	0.001	0.03	0	2.25
Montenegro	2.29	0.57	0.018	0.36	1	2.44
Poland	1.45	1.34	0.063	0.40	5	3.43
Romania	1.83	0.38	0.045	0.19	6	2.92
Russia	1.37	0.08	0.005	0.07	9	2.6
Serbia	2.56	0.5	0.046	0.29	1	2.74
Slovak Republic	1.28	0.92	0.074	0.71	2	3.14
Slovenia	1.15	1.95	0.060	0.79	1	3.08
Tajikistan	15.01	0.19	0.004	0.17	0	2.32
Turkey	1.69	0.47	0.012	0.12	11	3.37
Ukraine	4.01	0.28	0.036	0.31	6	2.71
Uzbekistan	7.43	0.19	0.010	0.12	1	2.63
Average	3.27	0.63	0.032	0.47	3	2.82

Source: Authors' computation

5 Results and discussion

5.1 Baseline regressions

In Table 4, we collect the empirical results of the *variance-components model*, reported in column (1) and the *random-intercept model* and the *random-coefficient model* with only firm-level variables, reported in Columns (2) and (3), respectively.[8] Fixed effects are reported for the intercept and the slopes in the upper part of the table, while the random effects are shown in the lower part of the table. All regressions include industry dummies. The LR test reported at the bottom

[8] We do also estimate the model by not imposing constant return to scale. The coefficient for labour is not statistically significant, thus confirming the validity of constant return to scale assumption.

of the table for each regression confirms that the multilevel model is preferred to the linear model.

The estimated coefficients ρ of ICC for each model, reported in the last row of the table, are statistically significant with a value of about 26% across regression models. This is evidence of the existence of a hierarchical structure in the data that needs to be modelled through a multilevel approach.

The *variance-components model* provides evidence of the existence of random effects at country-level. Firm productivity differs in mean by countries of about 0.76 standard deviation, which captures the unobserved country-level heterogeneity that will be further investigated in the next section. The random intercept is statistically significant at 5% level.

The *random-intercept model* with firm-level variables shows a reduction of level-1 residuals. The intercept has a magnitude of about 0.75 standard deviation from the mean, and it is statistically significant at 5% level. This indicates that there are differences across countries, which are related to a different country's context in which firms operate. At country-level, some firms have better performance, other worst. The measure is given by how widely the random-intercept is distributed around the estimated mean by country. The predicted country random-intercept lies for 44% of the countries in a range of [0.07, 1.36], meaning that, for these countries, there is a positive association between national context and labour productivity. Oppositely, for countries showing a negative predicted country random-intercept, the unobserved characteristics are related to lower labour productivity of firms with respect to the overall mean.

We start the discussion by looking first at fixed effects of firm-level variables as reported in column (3) for the *random-coefficient*. Particularly, capital has a positive and highly significant coefficient, suggesting that greater productivity is associated with higher investment intensity. start-up has a negative coefficient, suggesting that younger firms have lower labour productivity compared to more mature firms. Exporter has a positive and highly significant coefficient, providing evidence that greater labour productivity is associated with exporting firms. Qualification has a positive coefficient, suggesting that greater labour productivity is associated with higher qualified human capital. Finally, foreign has a positive coefficient, meaning that foreign participation in firm's assets is positively related to firm performance.

Turning attention to the random-coefficients, they are statistically significant at 1% level and the random intercept at 5% level. The random effects indicate how widely the estimated intercept and coefficients are distributed around the mean, shown in the fixed effects part. The estimated random effects for variables capital, start-up, export, qualification and foreign are largely widespread around their mean, which indicates that firms, given these internal characteristics, perform differently in different countries.

Figure 2 shows the predicted random effects of the country random-intercept, namely, the standard deviations of each country from the overall mean of labour productivity.[9] Firms show different labour productivity due to unobserved country-level factors, implying that such differences can be associated with a better or worse country context.

After controlling for firm-specific characteristics, large differences emerge among countries. Most EU emerging economies lie in the upper right-hand of the rank. These countries appear to be characterized by better conditions that might determine better business environments, also reflected in their higher firm performance.

5.2 The role of transport infrastructures and logistics

We collect in Table 5 the results of the *intercept-as-outcome model*, by which we assess the relationship between transport infrastructures and logistics variables and firm performance. Given the quite high correlation of country-level variables (see Appendix Tables 8, 9, 10, 11 and 12), we include them once at a time in the model.

The macro-control variable gap is negatively related to firm performance: it can be interpreted as the distance of the level of development of a given

[9] The predicted random effects are computed as the mean of the posterior distribution of the random effects with parameter estimates plugged in, known as Empirical Bayes predictors (Rabe-Hesketh and Skrondal, 2012).

Table 4 Results of variance-components model, random-intercept model and random-coefficient model

	Variance-components model		Random-intercept model		Random-coefficients model	
	(1)		(2)		(3)	
Fixed effects						
For intercept (β_{0j})						
Constant (γ_{00})	10.1653***	(0.1746)	9.6720***	(0.1740)	9.6792***	(0.1735)
For slopes ($\beta_{1j}\ldots\ \beta_{5j}$)						
Capital (γ_{1j})			0.0455***	(0.0035)	0.0449***	(0.0041)
Start-up (γ_{2j})			−0.0522	(0.0355)	−0.0948**	(0.0454)
Exporter (γ_{3j})			0.2038***	(0.0336)	0.1902***	(0.0497)
Qualification (γ_{4j})			0.0060***	(0.0005)	0.0055***	(0.0007)
Foreign (γ_{5j})			0.2875***	(0.0481)	0.2843***	(0.0686)
Sector dummies (δ_{0k})	Yes		Yes		Yes	
Random effects						
Constant (u_{0j})	0.7619**	(0.0964)	0.7536**	(0.0955)	0.7762**	(0.0960)
Capital (u_{1j})					0.0086***	(0.0088)
Start-up (u_{2j})					0.0904***	(0.0485)
Exporter (u_{3j})					0.1847***	(0.0518)
Qualification (u_{4j})					0.0025***	(0.0007)
Foreign (u_{5j})					0.2501***	(0.0700)
Residuals	1.3067***	(0.0088)	1.2805***	(0.0087)	1.2744***	(0.0087)
Log likelihood	−18,545.16		−18,324.25		−18,305.53	
Level 1 firms	10,954		10,954		10,954	
Level 2 countries	32		32		32	
LR test	2467.20***		2197.15***		2234.59***	
ICC	0.254	(0.048)	0.257	(0.048)	0.256	(0.049)

Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.10$

country from the most developed country in the sample, so that the larger the gap the worse the performance of firms in that country. Additionally, gap is negatively correlated with all the transport infrastructures and logistics variables, suggesting that less developed countries have also worse transport infrastructure endowment.

The variables road and rail show positive and statistically significant coefficients at levels 1% and 5% of confidence, respectively (see columns (1) and (2)). Therefore, Hypothesis 1 is fully supported. The extension of the road and rail networks explains firm performance heterogeneity across countries. Particularly, the road network significantly reduces the random intercept to about 0.38 standard deviation from the overall sales mean.

Our results are consistent with previous evidence on transport networks and firm performance in emerging economies, particularly with Wang et al. (2018) showing a positive relationship between city road density and firm-level innovation. From a more aggregate perspective, results are also in line with Bottasso et al. (2022), showing a positive relationship between road networks and knowledge spillovers in Italian regions, but partially differ from Audretsch et al. (2015). The latter find that road infrastructures have little or no effect on firm creation, possibly attributable to the high density of motorway networks in Germany, while, in emerging economies, road networks are remarkably less developed; thus, their improvement is likely to promote firms' activities.

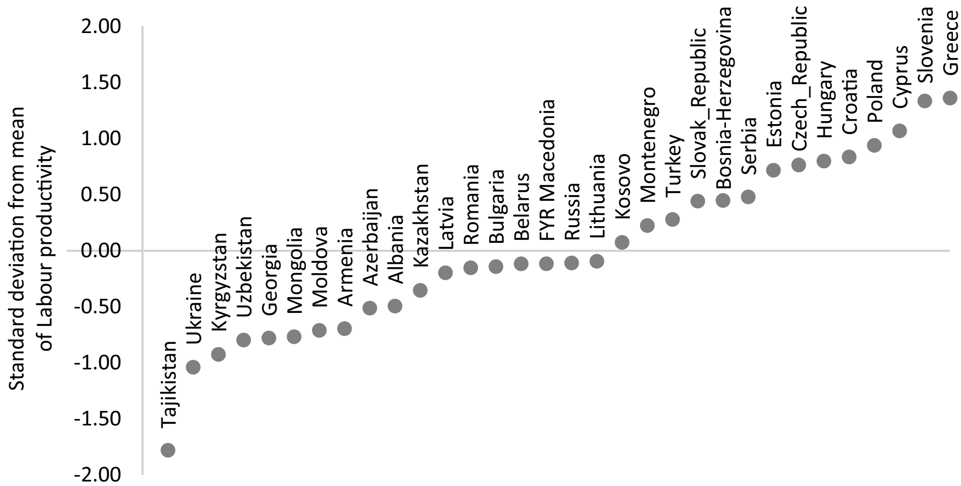

Fig 2 Ranking of country-predicted random effects (intercept of random-coefficients model)

The variable airport has a positive and significant coefficient at 1% level of confidence, while the coefficient of the variable port is not statistically significant (see columns (3) and (4)). It follows that Hypothesis 2 is partially and weakly supported, only with respect to the positive role of airports. In this case, part of the variability at country-level remains unexplained, due to other national factors possibly associated with it. It should be noted that other papers, using different measures for airport activities, such as passenger flows or number of destinations (Bilotkach, 2015), obtain stronger positive evidence. Overall, we argue that the presence of airports is positively associated with firm performance also by favouring international knowledge spillovers (Simmie, 2002; Bascavusoglu-Moreau and Li (2013). The non-significant role of ports is not in line with Bottasso et al. (2014), probably because of the different measure used, namely, port throughput. Unfortunately, for the emerging economies considered, there is a lack of other indicators of port infrastructure (such as length of quays, berths capacity or occupational profile).

The variable LPI has a positive and significant coefficient at 1% level of confidence (see column (5)). Therefore, Hypothesis 3 is strongly confirmed. A more developed logistic system of a country, by giving to firms transaction cost advantages in organizing an appropriate distributive channel, can contribute to enhance the relationship-building process between business partners. In other words, the performance of a country's logistic system is positively associated with the performance of firms by reducing time and distance in the supply chains and by generating knowledge spillover benefits between business partners, both domestically and internationally.

After country-level variables are introduced, the coefficient of the intercept decreases considerably. The estimated value of the random intercept remains significant meaning that other country factors matter for firm performance. The intra-class correlations confirm the role of national transport infrastructure variables in explaining part of the unexplained variability of firm performance among countries. The intra-class correlations decrease up to 0.081 compared to 0.256 for the random-coefficient model. This allows to argue that an important part of firm's labour productivity is surely explained by firm-level characteristics, but part of country-level variance is explained by transport infrastructures and logistic system and services, with specific aspects, such as road, rail, airport and logistics, being associated with better economic performance at the firm-level.

Table 5 Results of *intercept-as-outcome models* with infrastructures' country-level predictors

	Intercept-as-outcome models									
	(1)		(2)		(3)		(4)		(5)	
Fixed effects										
For intercept (β_{0j})										
Constant (γ_{00})	9.5952***	(0.1829)	9.7462***	(0.2143)	9.7493***	(0.2050)	10.0402***	(0.2236)	7.2651***	(0.8529)
Gap (γ_{10})	−0.0447***	(0.0090)	−0.0514***	(0.0106)	−0.0519***	(0.0104)	−0.0605***	(0.0118)	−0.0504***	(0.0100)
Road (γ_{20})	0.6482***	(0.1351)								
Rail (γ_{30})			8.5638**	(3.5558)						
Airport (γ_{40})					0.0006***	(0.0002)				
Port (γ_{50})							0.0238	(0.0358)		
LPI (γ_{60})									0.9836***	(0.2864)
For slopes ($\beta_{1j}\ldots\ \beta_{5j}$)										
Capital (γ_{1j})	0.0454***	(0.0040)	0.0460***	(0.0040)	0.0452***	(0.0041)	0.0452***	(0.0041)	0.0460***	(0.0041)
Start-up (γ_{2j})	−0.0943**	(0.0454)	−0.0913**	(0.0456)	−0.0946**	(0.0455)	−0.0941**	(0.0453)	−0.0935**	(0.0471)
Exporter (γ_{3j})	0.1884***	(0.0486)	0.1945***	(0.0498)	0.1900***	(0.0487)	0.1913***	(0.0493)	0.1862***	(0.0494)
Qualification (γ_{4j})	0.0055***	(0.0007)	0.0056***	(0.0007)	0.0055***	(0.0007)	0.0055***	(0.0007)	0.0055***	(0.0008)
Foreign (γ_{5j})	0.2829***	(0.0689)	0.2809***	(0.0689)	0.2851***	(0.0685)	0.2855***	(0.0686)	0.2699***	(0.0682)
Industry dummies (δ_{0k})	Yes		Yes		Yes		Yes		Yes	
Random effects										
Constant (u_{0j})	0.3790***	(0.0518)	0.4744***	(0.0616)	0.4477***	(0.0598)	0.5033***	(0.0662)	0.4219***	(0.0576)
Capital (u_{1j})	0.0076***	(0.0104)	0.0073***	(0.0108)	0.0087***	(0.0087)	0.0087***	(0.0088)	0.0078***	(0.0103)
Start-up (u_{2j})	0.0910***	(0.0489)	0.0898***	(0.0496)	0.0918***	(0.0493)	0.0900***	(0.0490)	0.0935***	(0.0516)
Exporter (u_{3j})	0.1760***	(0.0508)	0.1815***	(0.0524)	0.1765***	(0.0513)	0.1814***	(0.0515)	0.1772***	(0.0508)
Qualification (u_{4j})	0.0025***	(0.0007)	0.0026***	(0.0007)	0.0025***	(0.0007)	0.0026***	(0.0007)	0.0027***	(0.0007)
Foreign (u_{5j})	0.2520***	(0.0518)	0.2504***	(0.0702)	0.2496***	(0.0697)	0.2497***	(0.0698)	0.2379***	(0.0576)
Residuals	1.2745***	(0.0087)	1.2778***	(0.0088)	1.2745***	(0.0087)	1.2744***	(0.0087)	1.2842***	(0.0089)
Log likelihood	−18,284.80		−17,978.64		−18,289.75		−18,293.23		−17,768.38	
Level 1 firms	10,954		10,751		10,954		10,954		10,595	
Level 2 countries	32		31		32		32		31	
LR test	728.52***		965.92***		923.55***		1,121.67***		836.15***	
ICC	0.081	(0.020)	0.112	(0.027)	0.110	(0.026)	0.135	(0.031)	0.0974	(0.024)

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.10$

6 Robustness check

6.1 Bayesian model based on MCMC approach

To investigate the robustness of the previous analysis, the Bayesian model based on Markov chain Monte Carlo (MCMC) approach is computed in alternative to the frequentist analysis.

A multilevel problem concerns a population with a hierarchical structure. In samples from such a population can be described, the individual observations are in general not independent. For example, firms in the same country tend to perform similarly to each other, because of selection processes and because of the environment they share. In general, it occurs in survey research if the sample is not taken at random, but cluster sampling from geographical areas is used instead. It is also called "design effect". It depends on both intra-class correlation and cluster size. As a result, the average correlation among firms in the same country can be higher than the average correlations between firms operating in different countries. Standard statistical tests lean heavily in the assumption of independence of the observations. If this assumption is violated, and in multilevel data, this is almost always the case (Hox et al., 2017); the estimate of the standard errors of conventional statistical tests is much too small, resulting in many spuriously "significant" results. The biases that may be the effect of violation of the assumption of independent observation are still important assumptions to check (Hobert, 2000).

Our previous model is completely informed by the data: in this view, everything that we need to know for the model is encoded in the training data we have available, which gives a single point estimate for the output. This can be interpreted as the most likely estimate, given the data.

However, we might like to express our estimate as a distribution of possible values. The aim of the Bayesian approach is not to find the single "best" value of the model parameters, but rather to determine the posterior distribution for the model parameters.

A Bayesian model has two parts: a statistical model that describes the distribution of the response variable (y) given the unknown parameters (θ) of the model and a prior distribution that describes beliefs about the unknown parameters (θ) independent from the data, where the statistical model is the likelihood function $L(\theta; y)$. Therefore, not only the response is generated from a probability distribution, but the model parameters are assumed to come from a distribution as well. We have a *posterior distribution* for the model parameters that is proportional to the likelihood of the data multiplied by the *prior* probability of the parameters. The updating from the prior distribution to the posterior distribution is carried out using Bayes' theorem:

$$p(\theta|\mathbf{y}) \propto f(\mathbf{y}|\theta) \bullet \pi(\theta) = L(\theta|\mathbf{y}) \bullet \pi(\theta) \tag{4}$$

where $f(\mathbf{y}|\theta)$ is the sampling distribution of the response variable and $\pi(\theta)$ is the prior distribution of θ.

Bayesian methods explicitly use probability distributions to quantify uncertainties about the unknown parameters. Probability describes the degree of belief rather than long-run frequency. This is a considerable deviation from the classical statistics paradigm. As a result, Bayesian inference is carried out conditional on the observed data and does not rely on the assumption that a hypothetical infinite population of data exists.

We implement the Bayesian framework based on Markov chain Monte Carlo technique using Gibbs sampling algorithm. The analysis also compares the existence of the hierarchical structure of the data modelled through the multilevel approach with the linear regression model as reported in Table 6.

Despite coefficient parameters' estimates using the linear regression and the multilevel model being quite similar to the simulated posterior distribution of the parameters using the Bayesian approach, information about the fitted Bayesian model, as the average efficiency of the MCMC algorithm and marginal likelihood (ML),[10] the multilevel one results overwhelmingly more appropriate to describe the data. The efficiency summaries for any parameter using the Bayesian approach are reported in the Appendix (Tables 8, 9, 10, 11 and 12).

6.2 Alternative specification of the Cobb–Douglas production function

As mentioned in Section 3, due to the lack of information in the data on the cost of capital for the whole sample of firms, we proxy capital by

[10] The best fitted model is the one that represents the smallest marginal likelihood (ML)

Table 6 Bayesian MCMC estimations of linear and multilevel model

	Log of labour productivity (sales in USD/employee)							
	Linear regression model				Multilevel model			
	Simulated posterior distribution of the parameters		95% credible intervals		Simulated posterior distribution of the parameters		95% credible intervals	
	Mean	MCSE	Min.	Max.	Mean	MCSE	Min.	Max.
Firm-level variables								
Constant	9.0147	(0.0022)	8.9707	9.0608	9.6009	(0.0173)	9.3075	9.9156
Capital	0.0460	(0.0003)	0.0409	0.0505	0.0455	(0.0000)	0.0387	0.0524
Start-up	−0.0609	(0.0017)	−0.0956	−0.0275	−0.0524	(0.0003)	−0.1233	0.0175
Exporter	0.1968	(0.0033)	0.1538	0.2416	0.2040	(0.0003)	0.1391	0.2681
Qualification	0.0062	(0.0000)	0.0055	0.0070	0.0060	(0.0000)	0.0051	0.0069
Foreign	0.2885	(0.0056)	0.2027	0.3734	0.2870	(0.0003)	0.1928	0.3802
Sector dummies	Yes				Yes			
Country dummies	Yes							
Country clustered					Yes			
Random intercept					0.6238	(0.0014)	0.3715	1.0374
Av. efficiency	0.006527				0.7376			
Log marginal likelihood	-18,600.04				-18,316.28			
DIC	36,497.46				36,559.11			

Gibbs sampling is used for regression coefficients and variance components. MCMC sample size is 20,000. Default priors are used for model parameters

investments. However, BEEPS V for a sub-sample of firms provides information on the capital stock as well as on the cost of material and intermediate inputs. Therefore, we re-estimate the multilevel model by measuring the variable capital by the natural logarithm of the replacement cost for machinery, land and buildings per employee, and we also add the variable inputs as the natural logarithm of the total cost of raw materials and intermediate goods used in production (Audretsch et al., 2020). However, the estimation of random effects with a highly reduced number of observations available for the sub-sample (20.4% of the initial sample) does not allow to control for further explanatory variables and their related random effects. Therefore, we need to specify a more parsimonious model, in which, besides capital, inputs and industry-specific dummies, we introduce only transport infrastructures and logistics variables. As shown in Table 7, the estimations are fully consistent with the first specification of the Cobb–Douglas production function shown in Section 5.

7 Conclusions

The literature on entrepreneurship has focused on the ecosystems to shed light on the elements that can impact entrepreneurial activity (Acs et al., 2014, 2016, 2018; Stam, 2015; Alvedalen and Boschma, 2017; Brown and Mason, 2017; Stam and Spigel, 2018; Stam and van de Ven, 2021). In this regard, we embed the role of transport endowment as a part of the physical infrastructure in the entrepreneurial ecosystem literature (Audretsch et al., 2015). Indeed, transport infrastructures, by enhancing connectivity and interactions, facilitate the exchange of knowledge and ideas that could support entrepreneurship (Audretsch and Lehmann, 2005; Ghio et al., 2015; Audretsch et al., 2015). Previous studies have been mostly conducted

Table 7 Robustness check of Cobb–Douglas function with infrastructures' country-level predictors

	Intercept-as-outcome models: robustness check					
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed effects						
For intercept (β_{0j})						
Constant (γ_{00})	8.4717***	8.3966***	8.5624***	8.5166***	8.7310***	6.8867***
	(0.1970)	(0.2074)	(0.2295)	(0.2165)	(0.2321)	(0.7724)
Gap (γ_{10})		−0.0347***	−0.0408***	−0.0398***	−0.0461***	−0.0399***
		(0.0079)	(0.0093)	(0.0087)	(0.0098)	(0.0090)
Road (γ_{20})		0.5075***				
		(0.1185)				
Rail (γ_{30})			6.0397**			
			(3.0654)			
Airport (γ_{40})				0.0005***		
				(0.0002)		
Port (γ_{50})					0.0202	
					(0.0288)	
LPI (γ_{60})						0.6763***
						(0.2559)
For slopes ($\beta_{1j} \ldots \beta_{5j}$)						
Capital (γ_{1j})	0.0316***	0.0320***	0.0310***	0.0314***	0.0320***	0.0322***
	(0.0080)	(0.0079)	(0.0080)	(0.0079)	(0.0079)	(0.0080)
Inputs (γ_{2j})	0.1631***	0.1630***	0.1631***	0.1632***	0.1630***	0.1612***
	(0.0079)	(0.0079)	(0.0080)	(0.0079)	(0.0079)	(0.0080)
Industry dummies (δ_{0k})	Yes	Yes	Yes	Yes	Yes	Yes
Random effects						
Constant (u_{0j})	0.5754*	0.02991*	0.3692*	0.3435*	0.3903*	0.3489*
	(0.0788)	(0.0476)	(0.0557)	(0.0528)	(0.0576)	(0.0542)
Residuals	1.0279***	1.0278***	1.0301***	1.0280***	1.0279***	1.0306***
	(0.0154)	(0.0155)	(0.0156)	(0.0155)	(0.0155)	(0.0156)
Log likelihood	−3281.46	−3263.30	−3239.58	−3267.17	−3270.42	−3218.68
Level 1 firms	2238	2238	2215	2238	2238	2201
Level 2 countries	32	32	31	32	32	31
LR test	362.18***	106.29***	170.04***	146.71***	184.76***	125.65***
ICC	0.239	0.078	0.114	0.100	0.126	0.103
	(0.050)	(0.023)	(0.031)	(0.028)	(0.033)	(0.029)

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.10$

by adopting an aggregate perspective, while the channels through which transport endowment is related to firms' activities at micro-level remain overlooked especially for less developed countries.

With this work, we commit to shedding light on the relationship between country-level transport infrastructures and logistics system and services with the performance of firms from a micro-analysis perspective, while controlling for firm-level factors. Some studies focus on China, due to investments in improving the transport infrastructure system in recent years, while Eastern Europe and Central Asia countries miss this perspective of analysis. We consider different types of transport infrastructures, such as roads, railways, airports and ports, along with the overall performance of the country's logistics services.

In doing so, we adopt the appropriate approach to study a hierarchically structured phenomenon such as performance. The multilevel approach allows us to model the unobserved country-level heterogeneity in firms' labour productivity and to test whether it is related to different types of transport infrastructure in each country. To the best of our knowledge, this is the first study to examine whether a country's transport infrastructure is directly associated with the performance of enterprises in less developed economies.

Our results show that although most of the variability in firms' labour productivity is related to their internal characteristics, transport endowment also plays a role in their economic performance. More specifically, we find evidence that the extent of the road and rail transport networks has a strong positive relationship with firms' productivity. Moreover, the presence of airports and the performance of the logistics system of a country are also able to capture differences in performances across countries, while ports seem to have no influence on them.

This paper contributes to the literature on firm performance and transport economics by showing that the positive role of transport infrastructures on economic growth and development is also due to the positive relationship it has at firm-level. We argue that this process is particularly favoured by transport networks, promoting knowledge spillovers that, in turn, create business opportunities for entrepreneurs. It also highlights the role of transport infrastructure investments in emerging economies as a pathway to drive growth and accelerate the catch-up process. While in higher-income countries, investments in transport infrastructures mostly address the need for replacement and maintenance; in low-income countries, investments are needed to improve transport infrastructures and to bring them up to the level of those in more advanced economies (EBRD, 2018). A limitation of this study is that it does not take into account spillover effects among nearby areas, which might be relevant for a network industry. However, this can be seen as an avenue for future research.

Finally, this paper creates a paradigm for future studies to improve the understanding of the interdependence between different levels of analysis to design more complex and comprehensive transport investment strategies and logistics system and servicesdevelopment policies. We are aware, however, of the relevance that the availability of panel data over longer periods could have for determining the effect of changes in transport infrastructures on firm performance. In addition, the availability in the future of higher quality data for transport infrastructures, allowing a more detailed analysis of different types of networks and nodes, would improve research insights.

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Appendix

Table 8 summarise variables' definition and data sources. For further comments see section 3.

Table 8 Variables' definition and data sources

Variable	Description	Source
Dependent variable		
Labour productivity	Natural logarithm of total annual sales (converted in USD at the national annual exchange rates at the fiscal year 2011) per employee	BEEPS V (EBRD and World Bank)
Explanatory variables		
Firm-level		
Capital	Natural logarithm of the investments in fixed assets per employee	BEEPS V (EBRD and World Bank)
Start-up	Equal to 1 if the firm starts operations in the last 5 years, 0 otherwise	BEEPS V (EBRD and World Bank)
Exporter	Equal to 1 if the firm exports some of its outputs directly or indirectly, 0 otherwise	BEEPS V (EBRD and World Bank)
Qualification	Percentage share of permanent full-time employees holding a university degree	BEEPS V (EBRD and World Bank)
Foreign	Equal to 1 if 1% of assets or more are owned by private foreign individuals, companies or organizations, 0 otherwise	BEEPS V (EBRD and World Bank)
Country-level		
Gap	The ratio between the GDP per capita (in PPP constant 2011 international USD) of the most developed economy in the sample and the observed country	World Development Indicators (World Bank)
Road	Total roads in km per square km, including expressways, urban roads, paved and unpaved	Eurostat and Central Intelligence Agency (World Bank for country surface)
Rail	Total railways in km per square km, including public and non-public railways	Eurostat and Central Intelligence Agency (World Bank for country surface)
Airport	Number of airports paved per 1,000 square km.	Central Intelligence Agency (World Bank for country surface)
Port	Number of total ports, including the major seaports, river ports, container ports, oil terminals, LNG terminals	Central Intelligence Agency
LPI	The overall logistic performance index score	LPI Surveys (World Bank)

Table 9 investigates within and between variations of the dependent and independent variables. Due to the stratified nature of the data, large part of variation of firm-level variables occures within countries. Despite that, between variation of the latters has been investigated by including in the model firm level random coefficients.

Table 9 Descriptive statistics of firm-level variables clustered at the country-level

		Mean	Std. Dev.	Min	Max	Observations
Labour productivity ('000 USD/employee)	Overall	121.49	1020.97	0	73,700.00	$N = 10954$
	Between		104.44	22.20	498.48	$n = 32$
	Within		1017.11	−376.10	73,400.00	T-bar = 342.313
Capital ('000 USD/employee)	Overall	5.97	266.27	0	27,200.00	$N = 10954$
	Between		11.25	0.08	63.73	$n = 32$
	Within		265.99	−57.76	27,200.00	T-bar = 342.313
Start-up	Overall	0.15	0.36	0	1	$N = 10954$
	Between		0.09	0.01	0.35	$n = 32$
	Within		0.35	−0.20	1.15	T-bar = 342.313
Export	Overall	0.22	0.42	0	1	$N = 10954$
	Between		0.15	0.03	0.58	$n = 32$
	Within		0.39	−0.35	1.19	T-bar = 342.313
Qualification	Overall	32.67	30.81	0	100.00	$N = 10954$
	Between		13.40	9.62	59.47	$n = 32$
	Within		26.61	−26.80	123.04	T-bar = 342.313
Foreign	Overall	0.07	0.26	0	1	$N = 10954$
	Between		0.05	0	0.18	$n = 32$
	Within		0.26	−0.11	1.06	T-bar = 342.313

Table 10 shows correlation matrix among transport infrastructure variables. For these reason, the relationship between countries' transport endowment and firms' performance has been estimated separetly for each variable as shown in Table 7.

Table 10 Correlation matrix among country-level variables

	Gap	Road	Rail	Airport	Port	LPI
Gap	1					
Road	-0.45	1				
Rail	-0.43	0.71	1			
Airport	-0.41	0.57	0.70	1		
Port	-0.44	0.15	0.02	0.00	1	
LPI	-0.42	0.51	0.50	0.45	0.50	1

Tables 11 and 12 report effective sample sizes (ESS), correlation times, and efficiencies for model parameters after performing the Bayesian analysis for the OLS and the Multilevel model. We used 20,000 iterations to increase the accuracy of our simulation results (MCMC sample size = 20,000). The closer the ESS estimates are to the MCMC sample size, the better. Also, the lower the correlation times are and the higher the efficiencies are, the better. Results indicate that the multilevel model is more likely to be appropriate.

Table 11 Efficiency summaries: OLS model (MCMC sample size = 20,000)

	Log of labour productivity		
	ESS	Corr. time	Efficiency
Constant	22.4	892.8	0.0011
Capital	36.8	543.51	0.0018
Start-up	25.51	783.94	0.0013
Exporter	26.82	745.76	0.0013
Qualification	28.1	711.73	0.0014
Foreign	47.67	419.52	0.0024
Sector dummies			
Medium-high tech	24.04	831.89	0.0012
Medium-low tech	29.55	676.89	0.0015
Low tech	25.39	787.67	0.0013
Construction retail distribution	25	800.08	0.0012
KIBS	27.51	727	0.0014
Other services	45.34	441.12	0.0023
Country dummies			
Belarus	30.59	653.85	0.0015
Georgia	71.44	279.96	0.0036
Tajikistan	28.49	701.97	0.0014
Turkey	24.66	810.99	0.0012
Ukraine	36.99	540.67	0.0018
Uzbekistan	43.18	463.2	0.0022
Russia	26.19	763.56	0.0013
Poland	29.54	677	0.0015
Romania	23.33	857.35	0.0012
Serbia	39.99	500.11	0.002
Kazakhstan	41.67	480	0.0021
Moldova	23.52	850.44	0.0012
Bosnia and Herzegovina	22.89	873.63	0.0011
Azerbaijan	38.13	524.58	0.0019
FYR Macedonia	33.25	601.58	0.0017
Armenia	26.31	760.12	0.0013
Kyrgyz Republic	48.09	415.92	0.0024
Mongolia	34.71	576.27	0.0017
Estonia	37.52	533.03	0.0019
Kosovo	22.96	871.23	0.0011
Czech Republic	23.23	860.78	0.0012
Hungary	24.76	807.77	0.0012
Latvia	28.59	699.6	0.0014
Lithuania	31.12	642.61	0.0016
Slovak Republic	21.84	915.6	0.0011
Slovenia	27.08	738.49	0.0014
Bulgaria	28.33	705.93	0.0014
Croatia	22.75	879.25	0.0011
Montenegro	26.1	766.19	0.0013
Cyprus	21.98	909.78	0.0011
Greece	30.02	666.26	0.0015
Sigma2	4410	4.54	0.2205

Table 12 Efficiency summaries: multilevel model (MCMC sample size = 20,000)

	Log of labour productivity		
	ESS	Corr. time	Efficiency
Fixed effects			
Constant	79.74	250.8	0.004
Capital	11689.74	1.71	0.5845
Start-up	13438.04	1.49	0.6719
Exporter	10036.01	1.99	0.5018
Qualification	4575.38	4.37	0.2288
Foreign	18870.77	1.06	0.9435
Sector dummies			
Medium-high tech	19044.4	1.05	0.9522
Medium-low tech	18100.2	1.1	0.905
Low tech	18250.97	1.1	0.9125
Construction retail distribution	18577.88	1.08	0.9289
KIBS	20000	1	1
Other services	18956.74	1.06	0.9478
Random effects			
Constant	14913.33	1.34	0.7457
Sigma2	20000	1	1

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