Fin vs. tech: are trust and knowledge creation key ingredients in fintech start-up emergence and financing?

Theodor Florian Cojoianu ⬥ · Gordon L. Clark ·
Andreas G. F. Hoepner · Vladimir Pažitka · Dariusz
Wójcik

Abstract We investigate how the emergence of fintech start-ups and their financing is shaped by regional knowledge creation and lack of trust in financial services incumbents across 21 OECD countries, 226 regions and over the 2007–2014 period. We find that knowledge generated in the IT sector is much more salient for fostering new fintech start-ups than knowledge generated in the financial services sector. Additionally, the importance of new knowledge created in the financial services sector (IT sector) increases (decreases) as fintech start-ups grow and seek financing. When the level of trust in financial services incumbents falls within a region, this is followed by an increase in the financing provided to fintech start-ups. Nevertheless, regions with historically low average levels of trust in financial services incumbents attract less fintech investment overall.

Keywords Fintech · Entrepreneurship · Knowledge spillovers · Trust · Venture capital · Innovation

JEL classifications G20 · G24 · L26 · O30 · O31

T. F. Cojoianu · A. G. F. Hoepner
Michael Smurfit Graduate Business School & UCD Lochlann Quinn School of Business, University College Dublin, Carysfort Avenue, Blackrock, Co. Dublin, Ireland

A. G. F. Hoepner
e-mail: andreas.hoepner@ucd.ie

T. F. Cojoianu (✉) · G. L. Clark · V. Pažitka · D. Wójcik
School of Geography and the Environment, Oxford University, South Parks Road, Oxford OX 1 3QY, UK
e-mail: theodor.cojoianu@ucd.ie

G. L. Clark
e-mail: gordon.clark@smithschool.ox.ac.uk

V. Pažitka
e-mail: vladimir.pazitka@gmail.com

D. Wójcik
e-mail: dariusz.wojcik@spc.ox.ac.uk

G. L. Clark
Faculty of Business and Economics, Monash University, Melbourne, Australia

A. G. F. Hoepner
European Commission Technical Expert Group on Sustainable Finance, Brussels, Belgium

A. G. F. Hoepner
Stockholm School of Economics, Mistra Financial Systems (MFS), Stockholm, Sweden

🌱 Springer

1 Introduction

Information technology (IT) has long been at the core of the development of financial services. During the twentieth century, financial services have been transformed by the introduction of the ATM in 1967 by Barclays, followed by the transition from the analog era of financial technology to the digital era of electronic payment systems and the emergence of computerized securities trading and online banking (Arner et al. 2015; Wójcik and Cojoianu 2018). In the aftermath of the global financial crisis (GFC), we are witnessing the rise of a new wave of financial innovations, referred to as fintech, powered by advances in data science and computational power to store and analyse large financially relevant datasets. Legitimized by the low levels of trust in financial services incumbents compared to technology companies (Rooney 2018; Sapienza and Zingales 2012), one of the most visible features of the fintech movement has been the rise of innovative start-ups, which offer solutions ranging from mobile payments and automated investment advice to cryptocurrencies and crowdfunding platforms (Chen et al. 2019; Haddad and Hornuf 2019).

Given these new developments in financial intermediation, how can we best explain the spatial emergence of high-growth fintech start-ups? Resource-based theorists as well as innovation scholars have framed entrepreneurial knowledge and capacity to recognize new opportunities, as well as the ability to integrate new knowledge generated in incumbent organizations as the key factors in the emergence of new ventures and nascent industries (Acs et al. 2009; Alvarez and Busenitz 2007, 2001; Audretsch and Feldman 1996; Audretsch and Keilbach 2007; Qian and Acs 2013). One aspect which has been less explored in the literature is the relative importance of heterogenous knowledge sources and how they contribute to the emergence of new industries. In the case of emergence of fintech start-ups, it is unclear whether a region's IT knowledge and capabilities are more salient than the region's financial innovation capabilities in fostering new fintech start-ups.

On the other hand, institutional theorists have provided a complementary view explaining how new ventures in nascent industries gain legitimacy to access resources in the first place, in the absence of an economic track record (Bruton et al. 2010; Scott 2007; Sine and Lee 2009). Out of the three pillars of institutional theory, summarized by Scott (2007) as the regulative, cognitive and normative pillars, the first two have

received significantly more attention in studies linking entrepreneurship with institutional theory (Bruton et al. 2010). Recent evidence points towards the fact that social norms can also "act as a pull that influences potential entrepreneurs to believe not only that they could enter a new field, but that they should enter a new field because it is normatively legitimate and, thus, more likely to succeed" (York and Lenox 2014, p. 1936). Indeed, recent studies confirm that is the case across industries such as green buildings (York et al. 2018; York and Lenox 2014), clean technologies (Vedula et al. 2018) or responsible investment (Hoepner et al. 2019). While the literature has shown that emerging industries draw their legitimacy from supportive normative institutional logics, the literature has yet to show whether social norms that erode the credibility of established incumbents also confer legitimacy to potential disruption by start-ups. Our study aims to contribute to these gaps in the literature.

We investigate how new regional knowledge creation in both the IT and financial services sectors as well as the lack of trust in financial services incumbents shape the emergence and financing of fintech start-ups. The study spans across 21 countries, 226 OECD regions and between 2007 and 2014. While we find that knowledge generated in the IT sector is much more salient for fostering new fintech start-ups than knowledge generated in the financial services sector, we also find an increasing (decreasing) importance of new knowledge created in the financial services sector (IT sector) as fintech start-ups grow and seek financing. When the level of trust in financial services incumbents falls within a region, this is typically followed by an increase in the financing raised by fintech ventures. Nevertheless, regions with historically low average levels of trust in financial services incumbents attract less fintech investment overall. We employ a correlated random-effects estimator (Bell et al. 2019; Mundlak 1978; Schunck and Perales 2017), which allows us to distinguish between the effects due to within-region variation as well as between-region time-invariant effects of our explanatory variables on fintech start-up emergence and financing. Our results suggest that fintech emergence can be primarily explained by regional differences in the ability to consistently produce high levels of new knowledge and maintain above-average levels of human capital in the IT sector (between-region time-invariant effects), not due to the year-to-year variation in these factors within specific regions.

Our paper contributes to both theoretical development and empirical testing of resource-based theory (RBT), the knowledge spillover theory of entrepreneurship (KSTE) and institutional theory, in the context of the emerging fintech sector. By joining the research and insights of RBT with those of KSTE, we show that new knowledge created in different incumbent settings has a positive and dynamic effect throughout the entry and financing stages of start-ups. This builds on previous work of resource and knowledge theorists (Alvarez and Busenitz 2001; Audretsch and Feldman 1996; Audretsch and Keilbach 2007; Vedula et al. 2018), which considers these phenomena separately, and rarely distinguishes between different knowledge sources. Our research also expands on the work of institutional theory scholars, by theorizing and testing the impact of eroding trust in the incumbent financial sector on fintech start-up entry and financing. Our work further complements the theory and findings of Vedula et al. (2018) and York and Lenox (2014), who focus on social norms supportive of the emerging sector and less so on social norms de-legitimizing the incumbent sector, the latter of which is the focus of our study.

This paper is structured as follows. In Section 2, we draw on resource-based theory and institutional theory to formulate our hypotheses. Section 3 presents our empirical model and data. Section 3.2 provides the results of our empirical investigation, which are then discussed in the context of our theoretical grounding in Section 4. In Section 5, we outline the implications and conclusions of our work.

2 Theoretical background and hypotheses

2.1 A resource-based theory approach to knowledge spillovers and fintech entrepreneurship

Resource-based theory (RBT), one of the most prolific theories in explaining the competitive advantage of firms, argues that heterogenous resource bases of firms (both internal and external) and the ability of companies to command these resources are at the heart of competitive advantage (Barney 1991). Alvarez and Busenitz (2007, 2001) apply RBT to the study of entrepreneurship and contend that entrepreneurship is generally concerned with the ability of founders to recognize new opportunities and to acquire resources and recombine them into new products and services. The literature attributes the creation of heterogenous firms not only to the diversity of inputs but also to the heterogenous knowledge of entrepreneurs and their ability to coordinate disparate knowledge about technology, people and processes (Alvarez and Busenitz 2001). This raises the following questions: where does knowledge about new opportunities come from prior to the establishment of a new firm? Is knowledge generated outside the firm itself still relevant to the financing and further scaling of start-ups?

This enquiry has been led through the knowledge spillover theory of entrepreneurship (KSTE) literature, since its development by Audretsch (1995). KSTE suggests that an important source of entrepreneurship opportunities is new knowledge created in incumbent firms, universities or research organizations, which for various reasons remains uncommercialized (Acs et al. 2009; Audretsch and Keilbach 2007). The creation of new knowledge and its application towards the development of new products and services offer little certainty regarding the likelihood of success of its commercialization. Given this, Alvarez and Barney (2005) suggest that incumbents choose incremental innovation pathways and often disregard emerging opportunities characterized by a small customer base and limited revenue potential in the short term (Alvarez and Barney 2005; Christensen 1997; Christensen et al. 2018). Acs et al. (2009) further argue that it is the divergence in the valuation of new knowledge among new entrants and knowledge creators and the higher ability of new entrants to bear the costs of uncertainty associated with uncommercialized knowledge that enable entrepreneurs to pursue new opportunities.

However, how do entrepreneurs come into contact with new knowledge creation in incumbent firms to begin with? The appropriation of new knowledge by potential new entrants can occur through numerous channels, including supplier-customer relationships, formal and informal professional associations and the movement of highly skilled human capital. While new knowledge creation can be viewed as a stock, knowledge spillovers are dynamic processes, which vary over time and context (Feldman and Kelley 2006). There is considerable evidence that knowledge spillovers are localized (Audretsch and Lehmann 2005; Qian et al. 2013), particularly due to their reliance on human capital mobility and face-to-face interactions (Qian 2018). While some economic geographers argue that geographic proximity in itself is neither necessary nor sufficient for knowledge spillovers to occur, there is wide

agreement that geographic proximity reduces the cost of accessing and absorbing tacit knowledge (Audretsch and Feldman 1996; Audretsch and Lehmann 2005). Delgado et al. (2010) show that geographically concentrated clusters can lower the costs of entry for entrepreneurs through specialized supplier networks and facilitate access to early-adopter consumers, who are crucial for start-ups to validate their business models. Nevertheless, within-region variation in new knowledge creation depends on regional research facilities and investments in new knowledge-generating projects among other factors (Braunerhjelm and Feldman 2007; Delgado et al. 2010; Vedula et al. 2018).

While the importance of new knowledge creation for the emergence of new ventures has been established, the literature has yet to substantially address the relevance and characteristics of knowledge creators for entrepreneurship outcomes. These characteristics are particularly relevant for start-ups exploiting IT developments, which have emerged in the past 10 years. In particular, advances in data science have allowed for a wide array of applications, including in the financial sector, giving rise to the most recent phase of the fintech phenomenon (Chen et al. 2019). RBT suggests that heterogenous knowledge sources (financial sector vs. IT incumbent sectors) are likely to impact differently the emergence of the fintech sector and the types of start-ups that they foster. On the other hand, KSTE predicts that a higher stock of new knowledge is likely to lead to increased entrepreneurship opportunities; hence, we expect both the influence of knowledge generated in the IT sector and that generated in the financial sector to be positive on new fintech entrepreneurship (Chen et al. 2019; Wójcik and Cojoianu 2018) Hence, we hypothesize that:

> *H.1a. Regional knowledge created in the IT sector is positively related to regional fintech venture creation and financing.*
> *H.1b. Regional knowledge created in the financial services sector is positively related to regional fintech venture creation and financing.*

RBT also emphasizes the importance of human capital for start-ups, particularly in the context of human capital's ability to accumulate, store and disseminate tacit knowledge, which is often hard to access and can be a significant source of competitive advantage (Acs and Armington 2004; Barney et al. 2011; Gimeno et al.

1997; Marvel et al. 2016). The dynamic knowledge spillover process also depends on the capacity of potential new entrants to absorb newly created knowledge and to employ it in a commercial context (Cohen and Levinthal 1990; Qian 2018; Qian and Acs 2013). Industries that depend on knowledge spillovers, such as the IT (Braunerhjelm and Feldman 2007) and the financial sectors, rely on skilled workers to contextualize and recombine knowledge for new innovations (Audretsch and Feldman 1996). Viewed through the lens of resource heterogeneity and RBT, variations in the availability of highly skilled human capital are expected to relate to entrepreneurship outcomes at the firm and regional level. At the stage of founding, or prior to founding, human capital in the context of entrepreneurship entry refers to the regional pool of potential entrepreneurs or the skills, knowledge and networks of individual entrepreneurs or founding teams (Marvel et al. 2016). Post-entry, this definition extends to encompass the firm's available human capital, both within and outside the organization as potential innovative labour pools to draw on in the growth and scale-up stage of ventures. Hence, with respect to fintech emergence, we hypothesize that:

> *H.2a. Regional IT sector workforce productivity is positively related to fintech venture creation and financing.*
> *H.2b. Regional financial services sector workforce productivity is positively related to fintech venture creation and financing.*

2.2 Social norms and lack of trust in financial services incumbents

Although RBT has gained much traction in explaining entrepreneurship phenomena, institutional theory has also been very insightful and complementary to RBT in the study of emerging industries (Bruton et al. 2010). Institutional theory frames start-up ventures, and organizations in general, as being grounded in the regulatory, social and cultural environments they operate in (Bruton et al. 2010; Scott 1995). Institutional theorists have been concerned with the process of gaining legitimacy by organizations through conforming to the institutional environment, which is understood broadly as both formal and informal sets of rules as well as implicit assumptions about how organizations and individuals

should act (Bruton et al. 2010; Scott 2007). Scott (2007) summarizes the three main pillars of institutional theory as follows: First, the regulative pillar features the influence of formal institutions or governments, who have the task of defining and enforcing the rules by which economic actors should abide. Second, the normative pillar refers to the value system and the norms associated with behaviours that organizations and individuals are expected to follow. Finally, the cognitive pillar applies to individual behaviours and refers to the rules that shape beliefs and actions (Bruton et al. 2010). Out of the three pillars, a significant part of the literature linking entrepreneurship and institutional theory has focused on the regulatory and cognitive pillars (Bruton et al. 2010; York and Lenox 2014).

Institutional theory provides the basis for understanding how entrepreneurs seek legitimacy for the new ventures and how these are affected by societal values and social norms (Meek et al. 2010; Pacheco et al. 2014; Vedula et al. 2018; York et al. 2016; York and Lenox 2014). Nascent industries often face a liability of newness (Bruton et al. 2010; Pacheco et al. 2014); hence, the process of gaining legitimacy in the absence of a formal regulatory environment relies on normative aspects of the social cultural environment. Unlike incumbents, who draw their legitimacy for securing resources from their established economic track record, new ventures seek normative legitimacy since they lack any evidence related to past economic or financial performance (Bruton et al. 2010; Meek et al. 2010; York and Lenox 2014). Scholars have proposed that social norms affect founding rates by altering the perceived likelihood of success of entrepreneurs in nascent industries which are normatively legitimate. This has been shown to be the case in the cleantech sector (Pacheco et al. 2014; Vedula et al. 2018; York and Lenox 2014) as well as in the emergence of the responsible investment movement (Hoepner et al. 2019), where "[p]revalent social norms supporting an emerging industry in a region will likely influence the propensity of potential entrepreneurs to perceive opportunity related to those norms" (York and Lenox 2014, p. 1936).

An underexplored topic in the literature is whether entrepreneurs rely not only on social norms which explicitly support their business models, but also from social norms which are eroding the legitimacy of the incumbent sector. In the case of the fintech movement, scholars have attributed its emergence to the lack of trust in financial services incumbents (Brostrrm et al. 2018; Rooney 2018; Sapienza and Zingales 2012; Wójcik and Cojoianu 2018);

there is no statistical evidence that this has been the case across regions and countries. Furthermore, it is unclear whether the fintech sector has fostered an identity which is distinct from the financial sector and whether the diminishing trust in financial services incumbents is beneficial or detrimental to new fintech start-up emergence and financing. In this light, we seek to test whether:

H.3. The level of trust in financial services incumbents is negatively related to fintech emergence and financing.

3 Data and methodology

3.1 Dependent variables

3.1.1 New regional fintech start-ups and fintech financing

The *new regional fintech start-ups* dependent variable is the annual count of new high-growth fintech entrants by region. We map high-growth start-ups to regions using companies' headquarters addresses obtained from Crunchbase and a mapping tool provided by the OECD which allows us to match company addresses with Territorial Level 2 (TL2 regions) of OECD countries (OECD 2018). This allows for international comparability given that national statistical offices use the OECD classification to collect different policy-relevant datasets and governments use these to set regional policies.

In retrieving a global sample of fintech start-ups, we rely on the Crunchbase[1] and CBInsights[2] commercial databases. Both companies provide data intelligence services on innovative start-ups to investors, companies and governments around the world. In this respect, the database consists of high-growth-potential and innovative companies rather than an aggregation of country-level business registries. Following the approach of Wójcik and Cojoianu (2018), we conduct extensive keyword searches on Crunchbase, and complement it with other companies covered only by CBInsights (See Appendix A.1).

We begin with a global sample of 5381 fintech start-ups founded between 2006 and 2016 for which data on head office locations is available. Two thousand five hundred

---

[1] https://www.crunchbase.com/
[2] https://www.cbinsights.com/

forty-seven companies (47%) of our sampled companies have also data available on their financing rounds.

We then restrict our sample to companies headquartered across 21 OECD countries and 226 TL2 regions over the period 2007–2014, for which we were able to obtain sufficient data on our explanatory variables. Our final sample therefore covers 3081 new fintech ventures and their associated financing rounds (for 1718 companies, we are able to retrieve 4199 funding rounds). Our explanatory variables are lagged one year and cover the period 2006–2013. To provide further context to our sampled companies, we examine their websites to check whether they have been correctly classified as fintech start-ups by Crunchbase and CBInsights and we classify them into fintech sub-sectors based on the nature of their activities. We detail these fintech sub-sectors in Appendix A.2. In addition, we check their websites and record what kind of business models these start-ups pursue (business to business—B2B or business to consumer—B2C).

Using the headquarters location of the start-up at founding, we also map all the venture capital, private equity and venture debt funding rounds in fintech by region, using data from Crunchbase. We also quantify regional fintech start-up investment by fintech sub-sector and business model.

3.2 Explanatory variables

3.2.1 New regional knowledge creation in financial services incumbents

We construct a regional variable of new knowledge creation in financial services incumbents based on the fractional count of patent applications of asset managers, banks, insurance companies and stock exchanges across our 21 target countries and 226 regions. The fractional counts are based on inventor address or, where this was not available, on the applicant's address. For example, if a given patent has only one inventor, the region where the inventor is based will be assigned the value of 1 (i.e. we assign the full credit of new knowledge created only to a specific region). If a patent has two inventors located in different regions (e.g. one is from New York and one is from London), then each region gets assigned only a fraction of the credit for generating new knowledge (in this case 0.5 for New

York and 0.5 for London). The same rationale is applied when there are three or more inventors across different regions. We include patent applications who have an asset manager, a bank, a stock exchange or an insurance company as either the assignee or as the applicant.

We conduct patent searches using the PatSeer[3] platform, which links patents with the companies that own them. We first build our representative sample of financial services incumbents which includes the top 500 asset managers by assets under management in 2016 (TOWERS WATSON 2015), the world's top 2000 investment and commercial banks by fees between 2000 and 2015, a list of 776 listed insurance companies which we identified by using the SASB[4] industry classification database and a list of 186 stock exchanges from around the world from Datastream. The commercial and investment banking dataset was built using Dealogic[5] data and includes all banks with more than $4.8 million in total fees over the 2000–2015 period.

We review the identified patents from PatSeer covering the above sample of financial services incumbents to determine which are related to fintech and to categorize innovations into the seven fintech sub-sectors, which we used to classify the fintech start-ups sample. We then shortlist the patents and map each patent to the region(s) of innovator/applicant to create a fractional count.

3.2.2 New regional knowledge creation in the IT sector

We use the fractional regional patent application counts in the IT sector as a proxy for new regional IT knowledge. Regional IT patent data was collected from the OECD REGPAT database which allows for quantification of the innovation output over more than 2000 TL3 regions in the OECD and across several technologies. The OECD employs robust patent search methodologies to identify all patent applications to the EPO, USPTO and JPO as well as those filed under the Patent Cooperation Treaty (PCT).

From this total regional IT patent application count, we subtract the regional IT patent count in financial services incumbents to quantify the total new IT knowledge generated outside financial services incumbents. In this way, we can distinguish between the effects of both new IT knowledge generated in financial services

[3] www.patseer.com

[4] www.sasb.org/approach/sics
[5] https://www.dealogic.com/

incumbents as well as knowledge generated in the mainstream IT sector, on new fintech start-up creation.

3.2.3 Lack of trust in financial services incumbents

To measure the lack of trust in financial services incumbents, we use the Gallup World Poll cross-country dataset over the 2006–2013 timeframe. In particular, we use the statistic referring to the percentage of people answering "No" to the question in the Gallup Annual Survey: "In this country, do you trust financial institutions or banks?" The Gallup World Poll is designed to unveil comparable insights across countries and over time. For this particular question, given the sampling methodology of Gallup to interview approximately 1000 people from every country every year, we interpret it as a proxy for a general lack of trust measure of a country's population in the financial sector.

In this context, we define trust in financial services incumbents at best as the expectation that financial services incumbents act in the best interests of their (potential) clients, and at worst, as the expectation that individuals or organizations interacting with the financial sector will not be cheated (Guiso et al. 2008).

3.2.4 Regional workforce productivity in the IT and finance sectors

To study the relative influence of financial vs. technology workforce on fintech innovation, we measure the workforce productivity of both the IT sector and the financial and insurance sector at the regional level. We measure productivity as the ratio of the gross value added (GVA) to total employment within each sector. The data is retrieved from the OECD iLibrary.

3.3 Control variables

To control for the role of the demand for retail financial and insurance services, we use data from S&P Global on aggregate national volume of retail bank deposits and two variables from Oxford Economics—the percentage of household spending on (1) financial services and (2) insurance, aggregated also at the national level, given that comparable data is not available at the regional level. The country-level demand for investment banking services is constructed using data on capital market transactions and syndicated loans sourced from Dealogic databases. We aggregate deal values across

syndicated loans, M&As, equity and bond underwriting at the national level. We use the headquarter locations of companies raising money or involved in M&As to assign companies to countries.

We build an additional variable to control for regions hosting financial centres with high investment banking activity by quantifying the total fees of investment bank subsidiaries at the regional level. We use Dealogic data on investment banking fees, which are available at the transactional level, and hand collect the addresses of headquarters of investment banking subsidiaries from corporate websites, Bloomberg and Bureau van Dijk Orbis databases. We also use several regional- and country-level control variables to account for other factors which may influence fintech start-up entry. High-growth technology companies are known to be more likely to emerge in high-income regions (measured by GDP per capita), in regions which have higher availability of start-up capital (quantified by total equity and debt financing to start-ups from Crunchbase) as well as in regions with higher number of knowledge-producing organizations (measured by the number of research institutes per capita from the GRID[6] database).

Finally, we include the penetration of internet broadband and mobile phone subscription services per 100 people at the national level using data from the World Economic Forum and R&D expenditure as a percentage of GDP to measure country-level innovation-related spending (see Appendix A.3 for a summary of all variables).

3.4 Model specification

Our analysis is conducted at the regional level, with the data organized in a balanced panel between 2007 and 2014. The fintech start-up entry dependent variable is a non-negative count integer variable, while the annual regional fintech financing measure is a non-negative continuous variable.

Allison and Waterman (2002) show that a fixed-effects estimator is biased for a negative binomial model. Furthermore, fixed-effects models can only provide an estimation of within-cluster variation (in our case within-regional variation), and cannot estimate the effect of the average variation between regions (Schunck and Perales 2017). Random-effects models, on the other hand, assume that the within-cluster variation and

---

[6] https://www.grid.ac/

between-cluster variation are statistically the same. However, when this is not the case, the results of the random-effects model are often meaningless (Bell et al. 2019). The solution to these issues is to estimate a random-effects model which features time-varying co-variates expressed as deviations from the individual-specific means. This estimation strategy allows us to differentiate within- and between-regional effects, and thus, we can leverage the strengths of both random- and fixed-effects models (Bell et al. 2019; Schunck and Perales 2017). A between-within estimator used to estimate our econometric models is specified by Eq. 1 below:

$$y_{i,t} = \beta_W \left(x_{i,t} - \overline{x}_i \right) + \beta_B \overline{x}_i + \mu_t + \varepsilon_{i,t} \qquad (1)$$

In Eq. 1, the effect of the independent variable $x_{i,\,t}$ on $y_{i,\,t}$ is divided in β_W which represents the average within-region variation of $x_{i,\,t}$, and β_B which explains the remaining between-region average variation. The model in Eq. 1 can be re-written in a mathematical equivalent form as shown in Eqs. 2 and 3, so that the resulting coefficient on $\overline{x}_i$ represents the contextual effect (the average between-region effect while keeping $x_{i,\,t}$ constant), and β_W can be still interpreted as the average within-region variation of $x_{i,\,t}$. The model written in the form of Eq. 3 is also known as the correlated random-effects model (Wooldridge 2010) or the Mundlak model (Mundlak 1978; Schunck and Perales 2017).

$$y_{i,t} = \beta_W x_{i,t} - \beta_W \overline{x}_i + \beta_B \overline{x}_i + \mu_t + \varepsilon_{i,t} \qquad (2)$$

$$y_{i,t} = \beta_W x_{i,t} + (\beta_B - \beta_W) \overline{x}_i + \mu_t + \varepsilon_{i,t} \qquad (3)$$

Hence, we follow the Mundlak (1978) model (Eq. 3) and report both within-region effects (β_W) and contextual between-region effects ($\beta_B - \beta_W$), to understand the source of the variation that explains new founding rates as well as new regional financing amounts of fintech ventures. For new founding rates, we use a random-effect negative binomial Mundlak model, whereas for new regional fintech funding, we use a random-effect generalized linear Mundlak model (Schunck and Perales 2017). For robustness, we also cluster standard errors at the regional level for all models (Petersen 2009). We conduct robustness tests by excluding New York, California and London from our models to ensure that the results are not driven by these locations as they are the

most significant outliers when it comes to fintech start-up founding rates and investment, as well as new IT and financial sector incumbent knowledge creation. We also try alternative datasets for our control variables (particularly related to the availability of start-up funding from the World Bank and the World Economic Forum). To conduct further robustness checks, we also build an alternative variable of start-up funding at the country level ($ million) over 2006–2014 from Preqin, a leading data provider of intelligence in private financial market investment. The robustness tests using Preqin and World Economic Forum data are tabulated in Appendices A.6 and A.7, while the robustness tests which exclude New York, California and London have been conducted but not tabulated. All these tests are in line with the main findings. All regressors in our models are lagged by one year. Our results in this respect can be interpreted as a test of a relationship between start-up entry and financing and the key individual variables: new knowledge creation and lack of trust. However, the research design itself does not allow for direct testing of causality. We use the xthybrid STATA package which allows us to implement the Mundlak model (Schunck and Perales 2017).

4 Synthesis of results

4.1 Regional fintech entry

By examining model 1a (Table 1), we come across our first important insight, which is that average between-region effects are much stronger than within-region effects in driving fintech entry as far as new knowledge creation across both the IT and financial sector is concerned. The negative binomial model is a log-level model (with standardized independent variables, mean = 0 and sd = 1), and it is to be interpreted as a unit change in the independent variable and is related to a β change in the logged dependent variable ($\beta = \Delta (\ln Y_{x+1} - \ln Y_x)$). If we exponentiate both sides, this results in $\exp(\beta) = Y_{x+1}/Y_x$. This is the incidence rate ratio (IRR), which is interpreted as the relative increase of Y for one unit change in X (Vedula et al. 2018), where a one unit change is equivalent to 1 standard deviation change, given that sd (X) = 1.

Model 1a shows that within regions, the variation in new knowledge created in both the IT and financial services incumbents is positively related to new fintech

Table 1 Regional fintech start-up entry models

Dependent variable: number of new fintech start-ups by region	All fintech		B2B fintech		B2C fintech	
	Model 1a		Model 1b		Model 1c	
	Within-region variation	Between-region variation	Within-region variation	Between-region variation	Within-region variation	Between-region variation
New ICT incumbent knowledge creation	0.042***	0.541**	0.062***	0.425*	0.046	0.319
	(0.012)	(0.254)	(0.019)	(0.246)	(0.029)	(0.259)
New financial services incumbent knowledge creation	0.021***	0.116*	0.021	0.095	0.059***	−0.023
	(0.007)	(0.069)	(0.014)	(0.066)	(0.009)	(0.071)
Lack of trust	−0.116	−0.054	−0.096	−0.257	−0.327*	0.232
	(0.084)	(0.388)	(0.116)	(0.442)	(0.186)	(0.554)
Productivity financial and insurance sector	0.185*	−0.009	0.321**	−0.150	0.150	0.366
	(0.098)	(0.215)	(0.153)	(0.260)	(0.221)	(0.293)
Productivity IT sector	0.047	0.724***	−0.011	0.881***	0.034	0.664**
	(0.083)	(0.192)	(0.092)	(0.215)	(0.169)	(0.275)
Regional supply of investment banking services ($m)	−0.110	0.137	−0.105	0.158	−0.082	0.076
	(0.157)	(0.228)	(0.283)	(0.334)	(0.240)	(0.246)
Country demand for investment banking services ($m)	0.011	−0.783**	−0.150	−0.623*	0.032	−0.756*
	(0.104)	(0.323)	(0.147)	(0.361)	(0.195)	(0.386)
GDP per capita ($/capita)	−0.004	0.252	0.351	−0.209	0.364	−0.258
	(0.205)	(0.268)	(0.355)	(0.339)	(0.627)	(0.701)
Country R&D as % GDP	0.279	−0.046	−0.091	0.266	0.507	−0.197
	(0.360)	(0.467)	(0.505)	(0.581)	(0.766)	(0.856)
Broadband subscriptions	0.289	−0.719*	0.305	−0.753	0.543	−0.857
	(0.266)	(0.421)	(0.367)	(0.489)	(0.473)	(0.575)
Mobile subscriptions	−0.078	−0.235	−0.122	−0.123	0.104	−0.522
	(0.126)	(0.367)	(0.207)	(0.412)	(0.308)	(0.646)
Bank deposits ($bn)	0.090	0.899***	0.170	0.763**	−0.144	1.497***
	(0.108)	(0.286)	(0.172)	(0.308)	(0.293)	(0.533)
Retail fin. serv. spending % income	0.334	0.121	0.482	0.056	0.593	−0.490
	(0.228)	(0.404)	(0.345)	(0.528)	(0.475)	(0.592)
Retail insurance spending % income	0.387*	−0.102	0.278	0.040	0.296	0.084
	(0.234)	(0.302)	(0.372)	(0.422)	(0.643)	(0.637)
Regional fintech VC investment	0.006	−0.345	0.012*	−0.252	−0.008	0.009
	(0.005)	(0.486)	(0.007)	(0.450)	(0.008)	(0.455)
Research institutes per capita		0.030		0.002		0.153
		(0.148)		(0.141)		(0.144)
AIC	2422.365		2278.456		1223.561	
BIC	2636.864		2492.955		1438.06	
Loglikelihood	−1172.182		−1100.228		−572.7805	
Observations	1808		1808		1808	
Number of groups (regions)	226		226		226	

Cluster (region) robust standard errors in parentheses. Negative binomial log-level regression. Variables are standardized to mean 0 and sd = 1 for ease of interpretation. Coefficients can be interpreted as $\exp(\beta)$ = incidence rate ratio (IRR)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

venture emergence. A one standard deviation increase in the within-region mean in new IT knowledge created is related to a 4.2% increase in new fintech start-ups ($p < 0.01$). This is contrasted to a 2.1% positive effect due to new knowledge created in the financial services sector ($p < 0.01$). In addition, we find that a one standard deviation within-region increase in the productivity of the financial and insurance sector is related to a 20% increase in new fintech start-up entries ($p < 0.1$). We find no evidence that fintech emergence is related to within-regional variation of either lack of trust or regional IT sector productivity.

Between-region variation in our independent variables holds, however, the largest effect on new fintech start-up founding rates. A one standard deviation increase between regions in new ICT knowledge creation, new financial services knowledge creation and IT sector productivity is related to a 71% ($p < 0.05$), 12% ($p < 0.1$) and 106% ($p < 0.01$) increase in fintech founding rates between regions (model 1a, Table 1). This result underscores that the competitiveness of regions lies in the consistent generation of high levels of new knowledge rather than the variation from one year to the other in knowledge outputs. Hence, while we find support for both H.1a,b and H.2a, we can also draw the conclusion that the most salient factor determining the emergence of new fintech ventures is the sustained high output in new IT-related knowledge and the average productivity of the IT sector compared to other regions.

In models 1b and 1c (Table 1), we further analyse the entry determinants of fintech start-ups operating in two different customer segments: B2B vs. B2C. For the B2B sector, new regional IT knowledge creation both within and between regions is positively related to new B2B fintech founding rates. We do not find this, however, to be the case for the B2C sector, which is driven by the within-region variation in new financial services knowledge creation. Model 1c (Table 1) also shows that a standard deviation decrease in the level of trust leads to a 28% decrease in the number of new B2C fintech start-ups. This is initial evidence against H.3a and suggests that fintech B2C start-ups are negatively affected by the eroding trust in the incumbent financial sector.

4.2 Regional fintech financing

Regional fintech financing models (Tables 2 and 3) are log-log models, whose interpretation is the following: a 1% increase in the independent variable is related to a

β% variation in the dependent variable. In examining the determinants of regional fintech funding (models 2a–c, Table 2), we notice an overarching pattern: with respect to new knowledge creation, it is the average regional new knowledge creation in both the financial and IT sector that drives financing, and not the within-regional year-to-year variation in new knowledge outputs.

While for the fintech entry models, the effect of the between estimator of new IT knowledge creation was much larger than that of financial services new knowledge creation, we find the opposite holds true for the fintech investment models (models 2a–c). This result suggests that new knowledge created in the financial services sector becomes more and more important in the scale-up and financing process and as fintech solutions move from IT solutions applied to the financial sector to seamlessly integrated financial technology solutions. We also find evidence that only the between-region variation in IT workforce productivity is related to fintech start-up financing ($\beta = 0.724$, $p < 0.01$), and unrelated to the financial services workforce productivity.

An interesting finding that provides a more nuanced answer than perhaps we asked through H.3 is related to the effect of the lack of trust in financial services incumbents on the fintech financing (model 2a, Table 2). We find that an increase in the lack of trust in financial services incumbents within a region is related to an increase in the financing amounts of fintech ventures ($\beta = 0.35$, $p < 0.01$, model 2a). However, we find that regions situated in countries with low average levels of trust in financial services incumbents tend to attract less fintech financing overall ($\beta = -0.662$, $p < 0.01$; model 2a). This applies overall, as well as for start-ups that serve the B2B and B2C customer segments. The slight exception for investment in B2C fintech start-ups is that it does not seem to be negatively affected by the country's average level of trust in financial services incumbents (model 2c, Table 2).

In Table 3, we also test whether the overall findings from model 2a (Table 2) also apply to individual fintech sub-sectors. We find that this is indeed the case for start-ups in the data and digital infrastructure fintech sub-sectors. Investment in fintech start-ups that pursue technologies related to the back-office operations of incumbents (model 3a, Table 3, capital markets), seems to only be related to the between-region new knowledge created in the financial sector, which is intuitive, given the focus of the sub-sector. Trust does not appear to be

Table 2 Regional fintech start-up investment models

Dependent variable: ln (regional fintech start-up investment)	VC fintech		VC B2B		VC B2C	
	Model 2a		Model 2b		Model 2c	
	Within-region variation	Between-region variation	Within-region variation	Between-region variation	Within-region variation	Between-region variation
New ICT knowledge creation	− 0.018	0.171***	0.010	0.103***	− 0.035	0.084***
	(0.034)	(0.042)	(0.026)	(0.035)	(0.030)	(0.028)
New financial services knowledge creation	0.119	0.515***	0.120	0.433***	0.153	0.219**
	(0.133)	(0.145)	(0.133)	(0.136)	(0.109)	(0.100)
Lack of trust	0.350***	− 0.662***	0.314***	− 0.499***	0.148**	− 0.147
	(0.112)	(0.247)	(0.092)	(0.193)	(0.068)	(0.157)
Productivity financial and insurance sector	− 0.101	0.049	− 0.041	0.023	− 0.066	0.023
	(0.103)	(0.121)	(0.082)	(0.109)	(0.066)	(0.070)
Productivity IT sector	− 0.181	0.543**	− 0.136	0.343*	0.025	0.061
	(0.188)	(0.246)	(0.164)	(0.203)	(0.142)	(0.140)
GDP per capita ($/capita)	− 0.125	0.182	0.079	− 0.121	0.040	0.098
	(0.577)	(0.558)	(0.531)	(0.520)	(0.362)	(0.344)
Regional supply of investment banking services ($m)	− 0.020	0.009	0.002	− 0.012	− 0.031	0.026
	(0.045)	(0.046)	(0.041)	(0.041)	(0.029)	(0.027)
Country demand for investment banking services ($m)	− 0.019	0.048	0.006	0.036	− 0.012	0.001
	(0.050)	(0.066)	(0.048)	(0.059)	(0.045)	(0.043)
Country R&D as % GDP	− 1.195***	1.080***	− 0.918***	0.872***	− 0.534***	0.493***
	(0.253)	(0.271)	(0.218)	(0.239)	(0.133)	(0.137)
Broadband subscriptions	0.066	− 0.427**	0.052	− 0.285*	0.057	− 0.137
	(0.072)	(0.195)	(0.057)	(0.163)	(0.041)	(0.114)
Mobile subscriptions	1.467***	− 1.664***	0.970***	− 1.118***	0.450**	− 0.601**
	(0.358)	(0.416)	(0.296)	(0.346)	(0.220)	(0.251)
Bank deposits ($bn)	0.003	− 0.036	0.006	− 0.061	0.017	− 0.035
	(0.048)	(0.103)	(0.040)	(0.093)	(0.035)	(0.057)
Retail fin. serv. spending % income	− 0.064	0.185	− 0.016	0.082	0.007	− 0.002
	(0.236)	(0.241)	(0.178)	(0.176)	(0.138)	(0.147)
Retail insurance spending % income	− 0.925***	1.017***	− 0.674***	0.702***	− 0.340***	0.339***
	(0.187)	(0.212)	(0.149)	(0.166)	(0.112)	(0.125)
Research institutes per capita		− 0.106**		− 0.066		− 0.026
		(0.052)		(0.041)		(0.031)
AIC	3670.742		3055.726		2422.365	
BIC	3885.241		3270.225		2636.864	
Loglikelihood	− 1796.371		− 1488.863		− 1172.182	
Observations	1808		1808		1808	
Number of groups	226		226		226	

Cluster (region) robust standard errors in parentheses. Generalized linear log-log regression. Coefficients can be interpreted as 1% increase in independent variable is related to a β% variation in the dependent variable

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 3 Regional fintech start-up investment models across fintech sub-sectors

Dependent variable: ln (regional fintech start-up investment)	VC capital markets		VC data		VC digital infrastructure		VC IWM		VC payments	
	Model 3a		Model 3b		Model 3c		Model 3d		Model 3e	
	Within-region variation	Between-region variation	Within-region variation	Between-region variation	Within-region variation	Between-region variation	Within-region variation	Between-region variation	Within-region variation	Between-region variation
New ICT knowledge creation	0.010	− 0.003	0.015	0.034**	0.016	0.030*	− 0.036	0.087***	0.011	0.086***
	(0.013)	(0.011)	(0.018)	(0.015)	(0.020)	(0.018)	(0.025)	(0.033)	(0.025)	(0.030)
New financial services knowledge creation	0.036	0.358***	− 0.016	0.432***	0.122	0.189**	0.096	0.322***	0.172	0.125
	(0.056)	(0.097)	(0.077)	(0.110)	(0.111)	(0.094)	(0.100)	(0.116)	(0.125)	(0.138)
Lack of trust	0.089***	− 0.170**	0.226***	− 0.374***	0.206***	− 0.320**	0.114	− 0.295	0.094	− 0.218
	(0.031)	(0.070)	(0.068)	(0.111)	(0.063)	(0.138)	(0.076)	(0.206)	(0.084)	(0.177)
Productivity financial and insurance sector	− 0.006	− 0.008	− 0.023	− 0.015	− 0.062	0.016	− 0.030	− 0.041	− 0.000	0.049
	(0.043)	(0.061)	(0.047)	(0.066)	(0.048)	(0.064)	(0.060)	(0.076)	(0.066)	(0.081)
Productivity IT sector	0.023	0.037	− 0.042	0.170	− 0.087	0.222*	− 0.172	0.385*	− 0.068	0.187
	(0.080)	(0.088)	(0.103)	(0.108)	(0.109)	(0.118)	(0.147)	(0.203)	(0.152)	(0.178)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	512.2154		1823.922		2000.71		2482.415		2722.755	
BIC	726.7145		2038.421		2215.209		2696.914		2937.254	
Loglikelihood	− 217.1077		− 872.9609		− 961.3551		− 1202.208		− 1322.377	
Observations	1808		1808		1808		1808		1808	
Number of groups	226		226		226		226		226	

Cluster (region) robust standard errors in parentheses. Generalized linear log-log regression. Coefficients can be interpreted as 1% increase in independent variable is related to a $\beta\%$ variation in the dependent variable. The control variables included in the models above are GDP per capita ($/capita), regional supply of investment banking services ($m), country demand for investment banking services ($m), country R&D as % GDP, broadband subscriptions, mobile subscriptions, bank deposits ($bn), retail fin. serv. spending % income, retail insurance spending % income, research institutes per capita

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

material for either the investment and wealth management (IWM) start-up financing or for payment start-ups. The reason for this may be that a large proportion of these start-ups does not necessarily go into the new technology, but rather in capitalizing the investment or payment platforms themselves as investors in start-ups also become the first customers of fintech companies in these sub-sectors.

4.3 Robustness tests

In order to verify the robustness of our results, we conduct a series of robustness tests using data on venture capital availability indices derived from the World Bank and World Economic Forum (WEF) surveys, as well as

additional data on country-level venture capital investment from Preqin, one of the world's largest private intelligence providers. Our models using Preqin data, which covers all the countries and years in our original dataset, do not change the sign nor the statistical significance of our results for either fintech start-up entry or financing, except for B2C fintech entry, for which IT knowledge becomes a significant predictor. We believe this is due to the fact that, for robustness, when we replace our regional fintech investment variable from Crunchbase with the country-level start-up investment from Preqin, regional IT knowledge production also reflects some of the variation explained by regional fintech investment, and hence, it becomes significant. When using the WEF index on start-up availability,

given the more limited coverage of the indicator, we had to drop the year 2007 (226 observations) from our analysis. By doing so, our results remain unchanged for all the fintech start-up investment models, and hold for the majority of fintech entry results, with some minor discrepancies. As in the Preqin example, we believe these have to do with the different spatial scales (country vs. regional) at which these datasets are compiled. We consider our manually constructed regional variables to better capture variation in VC availability than compared to country variables which average out the effect across all regions.

5 Discussion

The determinants of fintech start-up emergence considered here provide us with several avenues for testing and contributing to RBT and institutional theory. First, we set out to test whether new regional knowledge creation in incumbent organizations is significantly and positively related to fintech start-up emergence. We find broad evidence to support this, and that new knowledge created in both the incumbent IT sector and the financial services sector is positively related to fintech start-up emergence. However, this effect is up to six times higher for the knowledge originating in the IT sector than the financial sector. What is interesting is that the reverse is true when examining the impact of regional knowledge stocks for fintech start-up financing. In other words, we find an increasing (decreasing) importance of new knowledge created in the financial services sector (IT sector) as fintech start-ups grow and seek financing. We also confirm an underlying assumption of RBT, which is that heterogenous firms will emerge, even in the context of homogenous inputs, as a consequence of the entrepreneur's ability to coordinate new and potentially disparate knowledge into new products and services (Alvarez and Busenitz 2007, 2001; Barney 1991). Given the same regional knowledge base, the emergence of B2B fintech start-ups draws exclusively from the new knowledge created in the IT sector, whereas the emergence of B2C fintech start-ups is exclusively influenced by new knowledge created in the financial sector. Hence, our study contributes not only to the emerging literature on fintech innovation (Chen et al. 2019; Haddad and Hornuf 2019) but also to RBT by highlighting regional IT knowledge and IT sector workforce productivity as key inputs for fintech entrepreneurship,

and the dynamic role that regional knowledge bases play throughout the start-up development process.

The second line of inquiry of our study is related to the impact of social norms, or the normative pillar of Scott (2007) on entrepreneurship. We hypothesized that the eroding trust in the financial sector may enhance the entry and financing prospects of new fintech start-ups. We find no statistically significant relationship between new fintech venture entry and the level of trust in financial services incumbents, besides in the case of B2C fintech ventures, where the lack of trust in financial services incumbents negatively impacts new fintech venture emergence. One potential explanation for this is that fintech ventures do not yet have a focused and distinct identity from the incumbent financial sector (see Khessina and Carroll 2008; York and Lenox 2014), and hence, potential entrepreneurs may perceive low levels of trust in the incumbent financial sector as a deterrent to starting a fintech venture. This is further confirmed by examining the impact of lack of trust in the financial sector on fintech venture financing. We find that regions with historical low average levels of trust in financial incumbents discourage the financing of fintech ventures. However, we also find robust evidence that when the lack of trust in financial services incumbents decreases within regions, this is followed by an increase in financing raised by fintech start-ups. In this sense, we also find evidence that fintech start-ups may gain legitimacy in the eyes of venture capitalists when societal trust in financial services incumbents decreases. Our study provides unique contributions relating to the application of institutional theory to entrepreneurship (Bruton et al. 2010; Meek et al. 2010; York and Lenox 2014), and shows that emerging social norms, which erode the licence of incumbents to operate can be a mechanism through which nascent industries can overcome their liability of newness. Equally, if the nascent industry does not forge a distinct identity from the incumbent sector, anti-incumbent social norms may also negatively affect the legitimacy of the nascent sector (Bruton et al. 2010; Pacheco et al. 2014).

Finally, through our use of the Mundlak (1978) model, we can distinguish whether fintech entry and financing is affected by within-region variation or between-region average variation of our explanatory variables. This has allowed us to show that regions, which consistently

produce substantial IT and financial knowledge and feature high average IT workforce productivity, have higher rates of fintech start-up emergence. Consequently, within-region incremental deviations from these means do not meaningfully affect regional capability to produce and finance more fintech start-ups. This is significant, as many previous studies have focused on explaining within-region variation (fixed effects) at the detriment of being able to identify between-region/time-invariant determinants of innovation outcomes.

Our results are subject to some limitations. We have identified several statistically significant relationships among variables of theoretical interest that link knowledge creation and lack of trust in financial services incumbents to fintech venture creation and financing. These statistical relationships are not sufficient to prove causality. Evidence of a causal relationship could also entail a difference-in-difference methodology using the financial crisis as an exogenous shock to which regions with higher IT knowledge rates and higher levels of distrust in financial services incumbents may respond by founding and financing more fintech start-ups. In our case, testing for this relationship in this way has not appeared sufficiently reliable given both data availability prior to the crisis and the emergence of the fintech sector primarily as a post crisis phenomenon. Nevertheless, previous literature on the topic of new regional knowledge creation and new venture entry confirms our results (Acs et al. 2009; Audretsch and Feldman 1996; Audretsch and Keilbach 2007; Cojoianu et al. 2020). To the best of our knowledge, there is no study analysing the impact of new regional knowledge creation on fintech venture financing and there is only limited empirical work on social norms and entrepreneurship (Vedula et al. 2018; York et al. 2018, 2016; York and Lenox 2014).

6 Conclusions

In this paper, we investigated how regional knowledge creation and lack of trust in financial services incumbents influence the emergence and financing of fintech start-ups across 21 OECD countries and 226 regions over the 2007–2014 period. We find that knowledge generated in the IT sector is much more salient for fostering new fintech start-ups than knowledge generated in the financial services sector. Additionally, we show that the importance of knowledge created in the financial services sector (IT sector) increases (decreases) as fintech start-ups grow and

seek financing. We also show that, when the level of trust in financial services incumbents falls within a region, this is followed by an increase in the amount of fintech venture financing. Despite this, regions with historically low average levels of trust in financial services incumbents attract less fintech investment overall. We have thus shown that the insights from RBT and KSTE are useful in explaining the spatial emergence of fintech and have further unveiled that new knowledge creation affects both new entry and financing of fintech start-ups. In contrast with previous studies, which explore the link between social norms supportive towards nascent industries and entrepreneurship (Meek et al. 2010; Vedula et al. 2018; York and Lenox 2014), we theorize that social norms that erode trust in incumbents may also legitimize the business models of new entrants.

The potential implications of our findings are manifold. Aspiring and present fintech entrepreneurs are likely to benefit from an enhanced awareness of how knowledge spillovers and the availability of highly skilled IT workforce can improve the prospects of new ventures as well as likelihood of obtaining financing. Both of these factors are highly relevant to the initial location choice of new ventures (Vedula et al. 2018). Furthermore, understanding how social norms influence the evolution of nascent sectors can also aid with location choice as well as the timing of entry and financing of fintech ventures. Policymakers are likely to benefit from an understanding of how social norms relate to the financial and technology sectors. Regulation is also likely to take different avenues depending on whether fintech companies are viewed as technology companies serving the financial sector or whether they are considered financial services companies themselves, thus being subject to the same financial regulation as financial services incumbents. The way fintech companies should be classified is yet to be established as the following examples illustrate. Funding Circle, the UK peer-to-peer lending platform that went public on the London Stock Exchange on the 28th of September, is classified as a software company under the ICB industry classification promoted by the exchange (London Stock Exchange 2018). PayPal, a more established payments fintech player, is classified as a financial administration company by ICB, whereas under the GICS classification it is an IT company providing data processing and outsourced services.[7] Our study also opens new avenues for innovation academics and institutional theorists by drawing the attention to

---

[7] Source: Bloomberg terminal as of 30 October 2018

institutional logics that erode the licence of incumbents to operate, rather than logics that are explicitly supportive of nascent industries. We believe that exploring the normative institutional angle and how it affects different entrepreneurship outcomes is a prolific area of research.

Our study is not without its limitations. We use patents as a measure of knowledge generated in the financial sector as well as in the IT sector, while aiming to study knowledge spillovers. The weakness of these measures is that it does not cover all innovations in the sector, as not all innovations are patented, particularly in the financial sector. Although we provide evidence from 21 countries and 226 regions, our data does not include several geographies that have been at the forefront of the fintech revolution in recent years, including China. Our English language bias may have inadvertently resulted in the omission of some fintech ventures from companies that did not have any English language websites or trade descriptions in the databases that we consulted. Furthermore, our study is unable to analyse empirically any policy initiative that aims to encourage fintech emergence or fintech innovation which is likely to impact both fintech relevant knowledge production or directly the founding and financing of new fintech ventures. Our measure of distrust in financial services incumbents is aggregated at the country level and may be biased towards potential retail customers of financial services rather than industry professionals expressing their views; hence, the results may be more reliable in the case of B2C estimations than in the case of B2B ones. We also expect a regional-level trust measure to provide more robust results towards inferring the impact of social norms on regional entrepreneurship. Last but not least, we are not able to differentiate between the backgrounds and location of different fintech founders which may provide further insights into the knowledge base that entrepreneurs draw on when deciding to start a new fintech venture. We leave these aspects as well as the design of a causal research setting for fintech emergence for further research.

References

Acs, Z. J., & Armington, C. (2004). The impact of geographic differences in human capital on service firm formation rates. *Journal of Urban Economics, 56*, 244–278. https://doi.org/10.1016/j.jue.2004.03.008.

Acs, Z. J., Audretsch, D. B., Braunerhjelm, P., & Carlsson, B. (2009). Knowledge spillover theory of entrepreneurship. *Small Business Economics, 32*, 15–30. https://doi.org/10.1007/s11187-008-9157-3.

Allison, P. D., & Waterman, R. P. (2002). Fixed-effects negative binomial regression models. *Sociological Methodology, 32*, 247–265.

Alvarez, S. A., & Barney, J. B. (2005). How do entrepreneurs organize firms under conditions of uncertainty? *J. Manage.* https://doi.org/10.1177/0149206305279486.

Alvarez, S. A., & Busenitz, L. W. (2001). The entrepreneurship of resource-based theory. *J. Manage., 27*, 755–775. https://doi.org/10.1016/S0149-2063(01)00122-2.

Alvarez, S. A., & Busenitz, L. W. (2007). The entrepreneurship of resource-based theory. *Entrepreneurship: Concepts, Theory and Perspective.* https://doi.org/10.1007/978-3-540-48543-8_10.

Arner, D. W., Barberis, J. N., & Buckley, R. P. (2015). The evolution of fintech: a new post-crisis paradigm? *SSRN Electron J., 47*, 1271–1320. https://doi.org/10.2139/ssrn.2676553.

Audretsch, D. B. (1995). *Innovation and industry evolution.* Cambridge MIT Press.

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review.*

Audretsch, D. B., & Keilbach, M. (2007). The theory of knowledge spillover entrepreneurship. *Journal of Management Studies, 44*, 1242–1254. https://doi.org/10.1111/j.1467-6486.2007.00722.x.

Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Res Policy, 34*, 1191–1202. https://doi.org/10.1016/j.respol.2005.03.012.

Barney, J. (1991). Firm resources and sustained competitive advantage. *J. Manage.* https://doi.org/10.1177/014920639101700108.

Barney, J. B., Ketchen, D. J., & Wright, M. (2011). The future of resource-based theory: revitalization or decline? *J. Manage.* https://doi.org/10.1177/0149206310391805.

Bell, A., Fairbrother, M., & Jones, K. (2019). Fixed and random effects models: making an informed choice. *Quality and Quantity, 53*, 1051–1074. https://doi.org/10.1007/s11135-018-0802-x.

Braunerhjelm, P., & Feldman, M. P. (2007). *Cluster genesis: technology-based industrial development.* Cluster Genesis: Technology-Based Industrial Development. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199207183.001.0001.

Brostrrm, A., Mohammadi, A., & Saiedi, E. (2018). Distrust in financial institutions and fintech adoption: the case of P2P loans. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3124301.

Bruton, G. D., Ahlstrom, D., & Li, H. L. (2010). Institutional theory and entrepreneurship: where are we now and where do we need to move in the future? *Entrepreneurship Theory and Practice.* https://doi.org/10.1111/j.1540-6520.2010.00390.x.

Chen, M. A., Wu, Q., & Yang, B. (2019). How valuable is fintech innovation? *Review of Financial Studies, 32*, 2062–2106. https://doi.org/10.1093/rfs/hhy130.

Christensen, C. M. (1997). *The innovator's dilemma: when new technologies cause great firms to fail (management of innovation and change) hardcover.* Harvard Business School Press. https://doi.org/10.1016/j.jbusres.2010.12.002.

Christensen, C. M., McDonald, R., Altman, E. J., & Palmer, J. E. (2018). Disruptive innovation: an intellectual history and directions for future research. *J. Manag. Stud.* https://doi.org/10.1111/joms.12349.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly, 35*, 128. https://doi.org/10.2307/2393553.

Cojoianu, T., Clark, G. L., Hoepner, A. G. F., Veneri, P., & Wojcik, D. (2020). Entrepreneurs for a low carbon world: how environmental knowledge and policy shape the creation and financing of green start-ups. *Research Policy.* https://doi.org/10.1016/j.respol.2020.103988.

Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography, 10*, 495–518. https://doi.org/10.1093/jeg/lbq010.

Feldman, M. P., & Kelley, M. R. (2006). The ex ante assessment of knowledge spillovers: government R&D policy, economic incentives and private firm behavior. *Research Policy, 35*, 1509–1521. https://doi.org/10.1016/j.respol.2006.09.019.

Gimeno, J., Folta, T. B., Cooper, A. C., & Woo, C. Y. (1997). Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly, 42*, 750–783. https://doi.org/10.2307/2393656.

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *J. Finance.* https://doi.org/10.1111/j.1540-6261.2008.01408.x.

Haddad, C., & Hornuf, L. (2019). The emergence of the global fintech market: economic and technological determinants. *Small Business Economics, 53*, 81–105. https://doi.org/10.1007/s11187-018-9991-x.

Hoepner, A. G. F., Majoch, A. A. A., & Zhou, X. Y. (2019). Does an asset owner's institutional setting influence its decision to sign the principles for responsible investment? *Journal of Business Ethics.* https://doi.org/10.1007/s10551-019-04191-y.

Khessina, O. M., & Carroll, G. R. (2008). Product demography of de novo and de alio firms in the optical disk drive industry, 1983-1999. *Organization Science.* https://doi.org/10.1287/orsc.1070.0301.

London Stock Exchange. (2018). Funding circle holdings Plc.

Marvel, M. R., Davis, J. L., & Sproul, C. R. (2016). Human capital and entrepreneurship research: a critical review and future directions. *Entrepreneurship Theory and Practice, 40*, 599–626. https://doi.org/10.1111/etap.12136.

Meek, W. R., Pacheco, D. F., & York, J. G. (2010). The impact of social norms on entrepreneurial action: evidence from the environmental entrepreneurship context. *Journal of Business Venturing.* https://doi.org/10.1016/j.jbusvent.2009.09.007.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econom. J. Econom. Soc., 69–85.*

OECD. (2018). *OECD territorial grids.* Paris.

Pacheco, D. F., York, J. G., & Hargrave, T. J. (2014). The coevolution of industries, social movements, and institutions: wind power in the United States. *Organization Science.* https://doi.org/10.1287/orsc.2014.0918.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: comparing approaches. *Review of Financial Studies, 22*, 435–480. https://doi.org/10.1093/rfs/hhn053.

Qian, H. (2018). Knowledge-based regional economic development: a synthetic review of knowledge spillovers, entrepreneurship, and entrepreneurial ecosystems. *Econ. Dev. Q.* https://doi.org/10.1177/0891242418760981.

Qian, H., & Acs, Z. J. (2013). An absorptive capacity theory of knowledge spillover entrepreneurship. *Small Business Economics, 40*, 185–197. https://doi.org/10.1007/s11187-011-9368-x.

Qian, H., Acs, Z. J., & Stough, R. R. (2013). Regional systems of entrepreneurship: the nexus of human capital, knowledge and new firm formation. *Journal of Economic Geography, 13*, 559–587. https://doi.org/10.1093/jeg/lbs009.

Rooney, K. (2018). After the crisis, a new generation puts its trust in tech over traditional banks [WWW document]. Cnbc. URL https://www.cnbc.com/2018/09/14/a-new-generation-puts-its-trust-in-tech-over-traditional-banks.html

Sapienza, P., & Zingales, L. (2012). A trust crisis. *International Review of Finance, 12*, 123–131. https://doi.org/10.1111/j.1468-2443.2012.01152.x.

Schunck, R., & Perales, F. (2017). Within- and between-cluster effects in generalized linear mixed models: a discussion of approaches and the xthybrid command. *The Stata Journal.* https://doi.org/10.1177/1536867x1701700106.

Scott, W. R. (1995). Institutions and organizations: foundations for organizational science. *America.*

Scott, W. R. (2007). *Institutions and organizations: ideas and interests.* Sage.

Sine, W. D., & Lee, B. H. (2009). Tilting at windmills? In *The environmental movement and the emergence of the U.S. wind energy sector. Adm. Sci. Q.* https://doi.org/10.2189/asqu.2009.54.1.123.

TOWERS WATSON. (2015). The 500 largest asset managers.

Vedula, S., York, J. G., & Corbett, A. C. (2018). *Through the looking-glass: the impact of regional institutional logics and knowledge pool characteristics on opportunity recognition and market entry*. Stud: J. Manag.

Wójcik, D., & Cojoianu, T. F. (2018). A global overview from a geographical perspective. *Int. Financ. Centres after Glob. Financ. Cris. Brexit, 207*.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

York, J. G., & Lenox, M. J. (2014). Exploring the sociocultural determinants of de novo versus de alio entry in emerging industries. *Strategic Management Journal, 35*, 1930–1951. https://doi.org/10.1002/smj.2187.

York, J. G., O'Neil, I., & Sarasvathy, S. D. (2016). Exploring environmental entrepreneurship: identity coupling, venture goals, and stakeholder incentives. *Journal of Management Studies, 53*, 695–737. https://doi.org/10.1111/joms.12198.

York, J. G., Vedula, S., & Lenox, M. J. (2018). IT's not easy building green: the impact of public policy, private actors, and regional logics on voluntary standards adoption. *The Academy of Management Journal*. https://doi.org/10.5465/amj.2015.0769.