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TECHNOLOGY CLUSTERS AMONG FINTECHS: EXPLORING THE SIGNALING OF TECHNOLOGY SCOPE AND THE ROLE OF REGULATION

Research in Progress

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Abstract

Financial technology ventures (FinTechs) use the latest technologies and act in a highly regulated industry. Yet, the technological scope of FinTechs and how this scope affects funding from investors remains unclear. Accordingly, research calls to examine the influence of technologies on the funding amount of FinTechs, especially in the context of different levels of regulatory freedom. We answer these questions by conducting an explorative cluster and regression analysis of 1,821 FinTechs and find three dominant clusters of FinTechs: technology newcomers, selective adopters, and full technology applicators. Technology newcomers have the lowest adoption rate of new technologies while full technology applicators combine several new technologies. Based on signaling theory and generalized linear models, we find that clusters significantly differ regarding their funding amount. However, we find that higher regulatory freedom decreases the differences between these clusters regarding the funding.

Keywords: technology cluster, regulation, FinTech, funding.

1 Introduction

The technology scope determines the digital business strategy (Bharadwaj *et al.*, 2013) and is especially relevant for new high-tech ventures like financial technology ventures (FinTechs) (Drasch, Schweizer and Urbach, 2018). FinTechs use the latest technologies like blockchain or artificial intelligence (e.g., Gomber, Koch and Siering, 2017; Gomber *et al.*, 2018). Gozman *et al.* (2018) define four common technologies among FinTechs: cloud banking/back-office technology, messaging/blockchain/distributed ledger technology, cybersecurity/identity management, and big data/artificial intelligence. However, FinTechs do not use single but combinations of multiple technologies and their current technology scope remains unclear. Research calls to understand FinTechs' technology scope to investigate the potential of multiple technology usage (Gomber, Koch and Siering, 2017). Thus, our first research question is: What is the current technology scope of FinTechs?

For investors, it is difficult to assess the technology portfolio of new ventures. Since they do not have perfect information, they face challenges of asymmetric information and could refrain from investing (e.g., Hoenen *et al.*, 2014; Hoenig and Henkel, 2015). Information asymmetry is relevant in the context of FinTechs, since these ventures use multiple technologies such that the assessment is difficult. For ventures, the funding from investors leads to higher growth and survival rates (e.g.,

Beckman, Burton and O'Reilly, 2007). Prior research uses signaling theory to show how signals reduce information asymmetry and influence funding decisions (Colombo, 2021). Technologies are such a signal. However, research largely neglects technology signaling (Zmud *et al.*, 2010). Technologies shape the value proposition of new ventures, but also entail risks and can have different signaling values when combined with each other. To investigate how technology scope signaling relates to funding, we first explore technology combinations employed by FinTechs. This is in line with research calls to understand technologies of FinTechs (Eickhoff, Muntermann and Weinrich, 2017; Gomber, Koch and Siering, 2017) and their relation with funding (Eickhoff, Muntermann and Weinrich, 2017; Gozman, Liebenau and Mangan, 2018). Thus, we pose the second research question: How does technology scope signaling relate to investors' funding decisions?

The environment is essential for signaling (Connelly *et al.*, 2011). One important environmental factor is the regulatory environment across countries. The regulatory environment is especially relevant for new emerging technologies, since regulators face trade-offs when trying to balance customer safety, the risks associated by investors, and innovation opportunities (e.g., Roca *et al.*, 2017). Recently, regulators, for instance, established FinTech licenses to operate in a country. Although this entails safety, higher regulations could improve the technology development. Research calls to investigate the role of regulation for FinTechs (e.g., Gomber, Koch and Siering, 2017; Hua, Huang and Zheng, 2019). Thus, our third research question asks: How does the level of regulatory freedom moderate the relationship between technology usage and funding amount?

We conduct an explorative cluster and regression analysis of 1,821 FinTechs. We contribute to theory on information systems (IS) and entrepreneurship in three ways. First, we discover three novel clusters among FinTechs that reflect their technology usage, which we name: technology newcomers, selective adopters, and full technology applicators. Technology newcomers have a low adoption rate of new technologies while full technology applicators combine technologies. Second, we contribute to signaling theory by showing how investors adjust their funding according to technologies usage. The clusters selective adopters and full technology applicators receive lower funding than technology newcomers. Third, we show how regulatory freedom changes the signaling environment. Through a cross-country comparison, we find that high regulatory freedom decreases cluster differences in terms of funding. Our research offers insights for FinTechs as well as policymakers. We show FinTechs that in order to get funded, signaling the use of technology combinations is not beneficial. We provide policymakers with transparency that a lower regulatory burden decreases differences between technology clusters regarding the received funding amount.

2 Financial Technologies and Regulation

2.1 Digital business strategies and the relevance of technology

The importance of technologies shaping strategy grows steadily. According to Bharadwaj *et al.* (2013, p. 471), "digital technologies [...] are fundamentally transforming business strategies, business processes, firm capabilities, products and services, and key interfirm relationships in extended business networks". Consequently, technologies have to be connected to the business strategy forming the digital business strategy (Bharadwaj *et al.*, 2013). Thus, technologies determine the business model of ventures. This is especially relevant for high-tech ventures like FinTechs.

Studies conduct cluster analyses of FinTechs (e.g., Gozman, Liebenau and Mangan, 2018). Gozman *et al.* (2018) define the four main technologies cloud banking/back-office technology, messaging/blockchain/ distributed ledger technology, cybersecurity/identity management, and big data/artificial intelligence. Research calls to understand technology combinations, specifically of FinTechs (Gomber, Koch and Siering, 2017), and the relationship with the funding of FinTechs (Eickhoff, Muntermann and Weinrich, 2017; Gozman, Liebenau and Mangan, 2018).

2.2 FinTech and regulation

One important, and often ignored environmental factor in the context of new ventures is the level of regulation across countries. Regulations are important, since they increase ventures' compliance costs and favorable regulation could lead to competitive advantages (e.g., Cumming and Schwienbacher, 2018). The level of regulation is especially relevant in the context of high-tech ventures and new emerging technologies. Regulators face trade-offs when trying to balance customer safety, the risks associated by investors, and innovation opportunities (e.g., Roca *et al.*, 2017). Consequently, research calls for investigations on the impact of regulations, especially in the context of FinTechs (e.g., Gomber, Koch and Siering, 2017; Hua, Huang and Zheng, 2019; Milian, 2019). These ventures act in a highly regulated environment, the financial industry (Leong *et al.*, 2017; Hodson, 2021). Thus, the potential effects of regulations on new ventures should be especially visible in the FinTech context.

3 Methodology

3.1 Sample and measures

We compile a data set of 1,821 FinTechs from the database Crunchbase which is used for FinTech cluster analysis in IS research (Eickhoff, Muntermann and Weinrich, 2017). We follow the FinTech Crunchbase classification of Cojoianu *et al.* (2020). Following Reese, Rieger and Engelen (2021), we include FinTechs with team and funding data. We consider FinTechs in the thirteen countries Brazil, Canada, China, France, Germany, India, Israel, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States of America. We retrieve the data in October 2020. Since Crunchbase collects data with a time lag, the data represents 2019 (e.g., Haddad and Hornuf, 2019).

Cluster Variables. The four technology choices we consider mirror those identified by research (Gozman, Liebenau and Mangan, 2018). Technology choices are captured by the four binary variables. To study whether FinTechs use a technology, we examine the descriptions and tags on Crunchbase used in research (Marra *et al.*, 2015; Edwards and Todtenhaupt, 2020). If the tags or descriptions indicate to one of the technologies, the binary technology variable takes the value 1.

Regulatory Freedom. Following previous FinTech research, we retrieve data on the moderator regulatory freedom from the Fraser Institute (Haddad and Hornuf, 2019; Kolokas *et al.*, 2020). This variable measures the degree of regulation limiting the freedom in credit, labor, and business markets per country with a lower value representing more regulatory restrictions.

Funding Amount. We measure the funding amount in Crunchbase as the sum of all funding rounds in US dollars (USD) (e.g., Guo, Lou and Pérez-Castrillo, 2015; Reese, Rieger and Engelen, 2021).

Control Variables. We control for venture age, size, location, management experience, and country entrepreneurship activity (TEA) following previous research (Thornhill, 2006; Cumming and Schwienbacher, 2018; Cumming and Johan, 2020; Fredström, Peltonen and Wincent, 2021). The size and age of a venture are well-used control variables in research (Thornhill, 2006). To control for differences in the venture team, we include a dummy variable for the prior working experience. To control for the venture location, we include a dummy variable center that takes the value 1 if the FinTech has its headquarter in a financial center (Cumming and Johan, 2020; Cumming and Schwienbacher, 2018). To capture differences in country environments, we control for the TEA (Fredström, Peltonen and Wincent, 2021).

3.2 Analysis

Following prior research, we use a two-step approach (Dushnitsky, Piva and Rossi-Lamastra, 2022). First, we conduct an explorative cluster analysis. Second, we conduct regression analyses. The cluster analysis groups FinTechs such that differences in one cluster are as low as possible while differences

between clusters are as high as possible (e.g., Dushnitsky, Piva and Rossi-Lamastra, 2022). We employ a common two-step clustering process (Jansen, Simsek and Cao, 2012; Short *et al.*, 2016). We first conduct a hierarchical cluster analysis (Ward, 1963) to determine the optimal cluster number by an analysis of the dendrogram and stopping rules (Duda, Hart and Stork, 2011). We use these results as a basis for the second step, a k-means clustering.

To investigate the relationship between technology clusters and funding, we use the research model in Figure 1. Following Reese, Rieger and Engelen (2021), we use generalized linear models (GLM) with a negative binomial distribution and a log link. To account for the selection of ventures with team data and funding, we use the Heckman selection model (Heckman, 1979). We use the availability of a venture’s email address as an instrumental variable. We use robust standard errors and winsorize the variables at the 1st and 99th percentiles of their distribution.

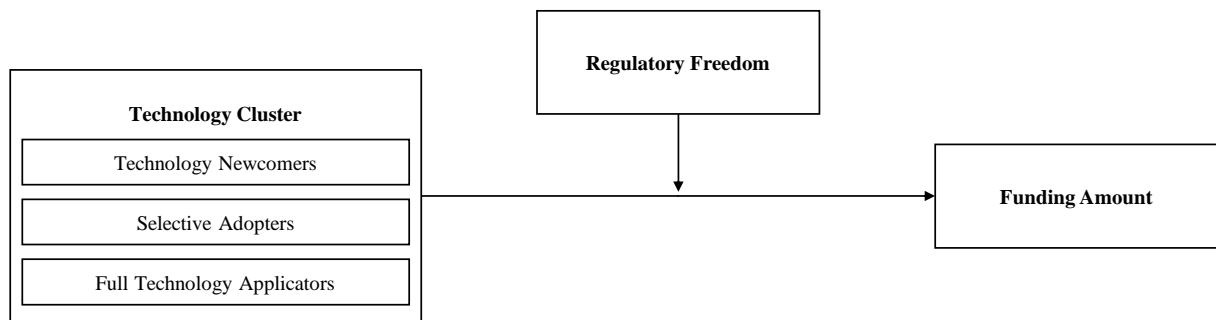


Figure 1. Research model.

4 Findings

4.1 Technology clusters

We find that technologies correlate with each other. This strengthens the need for a cluster analysis. The cluster analysis highlights three novel clusters of technology scope employed by FinTechs. We show the means of all technology variables by cluster in Table 1.

Cluster	Cloud	Blockchain	Cybersecurity	AI
Technology Newcomers n=883	0.000 (Low)	0.025 (Low)	0.022 (Low)	0.191 (Medium)
Selective Adopters n=461	1.000 (High)	0.128 (Medium)	0.039 (Low)	0.000 (Low)
Full Technology Applicants n=477	0.870 (High)	0.447 (High)	0.082 (Low)	1.000 (High)

Note: Value 0 indicates no adoption; value 1 indicates full adoption. Low means adoption <0.1; Medium means adoption >0.1<0.4; High means adoption >0.4; Cloud: cloud banking/back-office technology, Blockchain: messaging/blockchain/distributed ledger technology, Cybersecurity: cybersecurity/identity management, and AI: big data/artificial intelligence.

Table 1. Technology Representations by Cluster.

We observe that clusters significantly differ regarding the technology choices. The first cluster has low adoption rates of most technologies besides big data/artificial intelligence. Thus, we name this cluster technology newcomers. While the second cluster has a low adoption rate of big data/artificial intelligence and cybersecurity/identity management, it has a high adoption of cloud/back-office technology and a medium adoption of messaging/blockchain/distributed ledger technology. This cluster selectively adopts new technologies and is named selective adopters. The third cluster has a high adoption rate of cloud/back-office technology, messaging/blockchain/distributed ledger technology, and big data/artificial intelligence. It also has the highest adoption rate of cybersecurity/identity management technology. Thus, we name this cluster full technology applicants.

4.2 Funding performance and the moderating role of regulation

The approach of Kalnins (2018) and the variance inflation factors indicate that multicollinearity is not of concern for our variables. Table 2 reports the regression results with standardized variables. Model 1 includes all controls. Model 2 adds the technology cluster variables. We keep the first cluster technology newcomers as our omitted category. The coefficients of both technology clusters are negative and significant (Selective adopters: $b = -0.871$, $p < 0.001$; Full technology applicators: $b = -0.629$, $p < 0.001$). Thus, there are significant differences between the technology clusters regarding the funding. We conduct a Wald test that indicates a significant model fit improvement (Chi-Square = 63.08, $p < 0.001$). Model 3 adds regulatory freedom as an independent variable and Model 4 adds the interaction term between regulatory freedom and the clusters to the regression. The coefficient of the interaction term is positive, significant (Selective adopters: $b = 0.468$, $p < 0.001$; Full technology applicators: $b = 0.285$, $p < 0.1$), and improves the model fit (Chi-Square = 10.42, $p < .01$). Following Busenbark *et al.* (2021), we plot the marginal effects of the moderator on the relationship between technology clusters and the funding amount in Figure 2 and find the values significant for values of half a standard deviation below and above the mean. Thus, high regulatory freedom lowers the differences between the technology clusters.

Variables	Model 1	Model 2	Model 3	Model 4
Selective Adopters		-0.871*** (0.110)	-0.753*** (0.098)	-0.789*** (0.102)
Full Tech. Applicators		-0.629*** (0.121)	-0.554*** (0.108)	-0.567*** (0.113)
Regulatory Freedom			-0.314*** (0.089)	-0.452*** (0.118)
Sel. Adopters×Reg. Freedom				0.468*** (0.145)
Full Tech.×Reg. Freedom				0.285† (0.161)
Age	0.286*** (0.071)	0.227*** (0.060)	0.212*** (0.055)	0.197*** (0.054)
TEA	0.094* (0.048)	0.096* (0.043)	0.198*** (0.046)	0.190*** (0.044)
Mgmt. Experience	0.087 (0.317)	0.101 (0.270)	0.256 (0.257)	0.233 (0.255)
Financial Center	0.083 (0.105)	0.084 (0.095)	0.301** (0.091)	0.302** (0.093)
Inverse Mills Ratio	0.024 (0.207)	-0.028 (0.172)	-0.004 (0.160)	-0.016 (0.160)
Constant	15.053*** (0.262)	15.279*** (0.239)	14.933*** (0.190)	14.866*** (0.187)
Observations	1,821	1,821	1,821	1,821

Note: Standardized regression coefficients reported for non-dummy variables; Robust standard errors in parentheses; Full Tech.: Full Technology Applicators; Reg. Freedom: Regulatory Freedom; Mgmt. Experience: Management Experience; Size dummies included but not separately reported; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

Table 2. GLM Analysis Results (Dependent Variable: Funding amount).

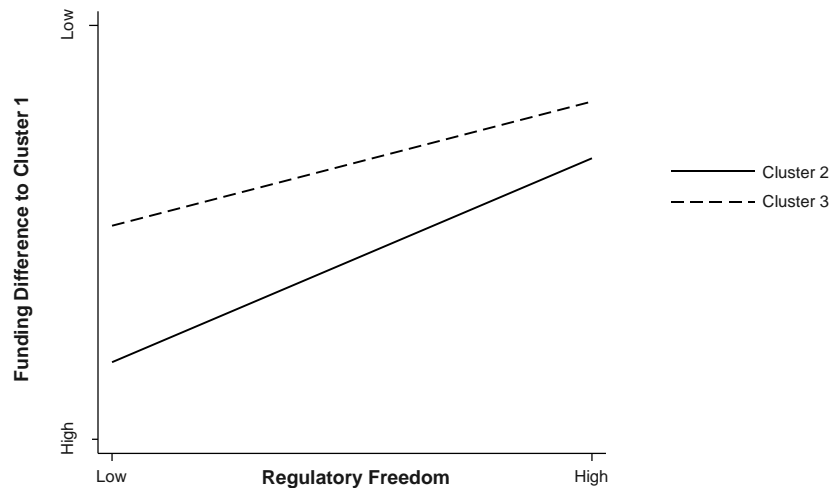


Figure 2. Relationship between Clusters and Funding Based on Regulatory Freedom.

We conduct numerous robustness and endogeneity tests. As an alternative measure of regulatory freedom, we use the financial freedom, focused on the financial sector (Heritage Foundation, 2021). We re-ran our models with a four-cluster solution, with funding values for the year 2020, and changed the matching algorithm. Finally, we include a variable into our models that captures the total difference between the FinTechs' technology choices and the cluster centroids (Dushnitsky, Piva and Rossi-Lamastra, 2022). We are always able to support our results. Some economies require FinTechs to obtain licenses. We use a dummy moderator that takes the value 1 if such a license is necessary for a country. We find that P2P and crowdfunding licenses even increase the differences between clusters regarding the funding. To check for reverse causality and control for endogeneity, we re-ran our analyses using funding as the independent and technology clusters as the dependent variable (Landis and Dunlap, 2000). We do not find statistically significant relationships for the moderator. Moreover, we include an endogeneity control variable following, for instance, Nadkarni and Chen (2014) and find our results remain robust.

5 Interpretation and Discussion

5.1 Insight 1: Three common technology scope clusters

We conduct a cluster analysis and find three novel technology scope clusters of FinTechs: (1) technology newcomers, (2) selective adopters, and (3) full technology applicators. We find practical examples for cluster 1 (Lendingkart), cluster 2 (Paystand), and cluster 3 (ABC Fintech/i2Chain).

Further, we examine differences between technology clusters regarding the service focus. Gozman *et al.* (2018) define six financial services pursued by FinTechs: payment; investment/asset management; finance/credit management; microfinancing/crowdfunding; new banking; and personal financial management. We find most clusters significantly differ regarding the service focus. Cluster 1 has the largest focus on banking services like investment/asset management and finance/credit management. In contrast, clusters 2 and 3 have a higher focus on financial services like payments, which “have always been at the forefront of technological change” (Gozman *et al.*, 2018: 234).

5.2 Insight 2: Relationship between technology clusters and funding

Due to information asymmetry, it is difficult to assess the technology portfolio of new ventures for investors. According to signaling theory, sending effective signals reduces information asymmetry (Spence, 1973). One form of signaling is technology signaling. This signal is costly, observable, and

has a high receiver attention. Our regression analysis shows that clusters with a larger technology scope receive a lower funding amount from investors.

Ventures trying to leverage new technologies need specific resources (Townsend and Busenitz, 2015). This increases the uncertainty for investors when evaluating the technology usage (Townsend and Busenitz, 2015; Barua and Mani, 2018). Since the outcome of ventures with new technologies is unpredictable, investors tend to invest a lower funding amount in these ventures (van de Vrande, Vanhaverbeke and Duysters, 2009). Prior IS research shows that multiple technology signals are not valued by investors (Zmud *et al.*, 2010). Thus, the signaling of a large technology scope decreases the signal fit, the extent to which a signal represents the underlying quality. Summing up, if FinTechs focus on technology breadth instead of depth, uncertainty arises among investors.

5.3 Insight 3: The moderating role of regulation

We respond to the calls to investigate the role of regulations on new ventures' entrepreneurship behavior (e.g., Bradley *et al.*, 2021) and FinTechs (e.g., Gomber, Koch and Siering, 2017). We find that the relationship between technology scope signaling and funding depends on the regulatory environment. In an environment with high regulatory freedom, investors are more likely to take risks and believe in the successful development of technologies.

Signaling theory describes the environment as essential as it changes the signal strength and calls for further research (Connelly *et al.*, 2011). Regulations are highly localized, differ between countries, and thereby create heterogeneous environments. We account for this by examining the regulatory freedom per country. In an environment with high local regulatory freedom, the development risks for new technologies are lower and thereby also the investor uncertainty. In the high-tech sector, upcoming changes are usually not predictable (van de Vrande, Vanhaverbeke and Duysters, 2009). One major preventer of technology development is the level of regulation. If at least the level of regulatory freedom favors the development of technology, the risks associated with new technologies is lower.

As a consequence, the technology scope signal fit (extent to which the large technology scope signal represents the quality of a successful development) is higher in an environment with high regulatory freedom. Thereby, information asymmetry between ventures and investors decreases. Thus, regulatory freedom increases the funding likelihood of high-tech ventures with a large technology scope.

5.4 Theoretical contributions and practical implications

We contribute to theory on the interface between IS and entrepreneurship literature in three ways. First, we explore novel clusters among FinTechs. While previous research identifies technologies employed by FinTechs (e.g., Gozman, Liebenau and Mangan, 2018), we explore combinations of these technologies. Thereby, we identify three dominant technology clusters: technology newcomers, selective adopters, and full technology applicators. The cluster technology newcomers has the lowest adoption rate of new technologies, while the cluster full technology applicators combines several new technologies. Hence, we explain that FinTechs have different technology scopes and, consequently, different digital business strategies. This needs to be considered in future research.

Second, we extend signaling theory (Spence, 1973) by showing how investors adjust their funding according to the technologies used by the target venture. We add to findings from previous literature on signaling in a high-tech context (e.g., Zmud *et al.*, 2010). We extend these results by not focusing on the number of signals but comparing the technology scopes of new high-tech ventures. We transfer the signaling of technologies to the context of new high-tech ventures in a highly regulated industry. Although the technologies we investigate may change in the future, the underlying insights remain relevant.

Third, we extend signaling theory by showing that regulatory freedom alters the environment for technology signaling. Signaling research calls to examine the role of the signaling environment

(Connelly *et al.*, 2011). Through a cross-country comparison, we contribute to regulation literature by showing how regulatory freedom influences the uncertainty of investors concerning new financial technologies. Higher regulatory freedom decreases differences in the funding amount received by FinTechs of different technology clusters. Summing up, we show that technology signaling in the form of technology scope and the level of regulatory freedom as a signaling environment are of high importance for new ventures.

Our research offers interesting insights for FinTechs as well as policymakers. We provide an overview of FinTechs' applied technology scope and show FinTechs that to get funded signaling a large technology scope is not beneficial. In addition, an environment with regulatory flexibility is promotional in signaling technology usage for a high funding amount. For policymakers, the regulation of new high-tech ventures is of major concern (Bollaert, Lopez-de-Silanes and Schwiendbacher, 2021). This research offers insights for policymakers on how to regulate FinTechs. We provide policymakers with transparency that less regulatory burden decreases differences between technology clusters regarding the funding. However, most regulatory licenses for FinTechs provided by policymakers do not reach their goal of reducing the uncertainty of investors. This research shows that policymakers should carefully evaluate strict regulations for new high-tech ventures, since these regulations can limit the tendency of investors to fund ventures with a high technology scope.

5.5 Limitations and avenues for further research

Our research does not come without limitations to be tackled by future research. First, our research focuses on FinTechs as new ventures in a highly regulated industry. To enhance the results of this research, future research could extend our model to other highly regulated industries. Second, we rely on the funding amount as our dependent variable. Future research could analyze financial indicators, such as profit, once FinTechs move into later life-cycle stages. Thereby, one could investigate if the effect of technology clusters goes beyond signaling towards investors. Third, the uncertainty towards new technologies and the venture outcome could decrease over time as the technology and the venture mature and investors get more knowledgeable of the technology potential (van de Vrande, Vanhaverbeke and Duysters, 2009). Thus, it would be fruitful for future research to obtain panel data and investigate how the technology clusters and their relation with funding change over time.

6 Conclusion

Sending signals is crucial for new high-tech ventures to obtain funding from investors. This research examines the relation between technology signaling of FinTechs and the funding amount. We contribute to FinTech literature by conducting an explorative cluster analysis and define three novel technology scope clusters. By drawing on signaling theory and the latest research results, we find that these technology clusters significantly differ regarding their relationship with the funding amount. Technology clusters with a larger technology scope receive less funding. However, in a cross-country comparison, we find that funding differences between technology clusters are lower in a context of high regulatory freedom. Regulatory freedom increases the likelihood of new high-tech ventures with a large technology scope getting funded by investors. We extend signaling theory by showing that technology scope signaling relates to funding and regulatory freedom alters the signaling environment in the context of new venture financing.

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