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Business models of FinTechs – Difference in similarity?

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ABSTRACT

The FinTech industry is gradually maturing and offers a wide range of financial services on the global stage. Still, the understanding of FinTech business models remains at its infancy with a shortage of cross-country comparisons. This paper aims to determine the differences in business model attributes of FinTechs in five rapidly emerging FinTech hotspots in Central and Eastern Europe (CEE). Survey results from Estonia, Latvia, Lithuania, Poland, and Russia, accompanied by cluster analysis, enable us to provide unique in-depth evidence on FinTech business models. Across the selected countries, we observe significant differences in the attributes of FinTech business models: key activities, key resources, value propositions, customer segments, delivery channels, cost structure, and revenue stream. We identify four clusters of FinTechs: “lending community”, “mixed services”, “payment service”, and “payment community”. Although these clusters share similarities with FinTech archetypes proposed in previous research, they remain rather unevenly distributed across countries.

1. Introduction

The application of innovative digital solutions for the provision of financial services has led to the rapid emergence of FinTech companies (hereafter FinTechs). These can be either start-ups or established companies with varying capabilities for either disrupting or contributing to the provision of traditional financial services. The overall influence of FinTech on the functioning of the financial sector relies heavily on the number of FinTechs as well as on the setup of their business models. Existing empirical studies indicate that there exists a significant variation in the count of FinTechs across countries (Haddad and Hornuf, 2019; Laidroo and Avarmaa, 2020). However, the determination of precise counts, including counts by types of activity, remains problematic, as there exists no universal definition and no universal classification system for FinTech (Iman, 2020). In terms of the FinTech business models, the literature remains highly scattered with no common understanding of their attributes. Some authors consider FinTech business model almost equivalent to the type of product/service provided by the company (e.g., Lee and Shin, 2018; Liu et al., 2020), while others acknowledge that it is based on a more diverse set of attributes (e.g., Lee and Teo, 2015; Eickhoff et al., 2017). In line with these arguments, a recent literature review by Iman (2020) emphasizes a need for further research into the characteristics and attributes of FinTech in different settings, and Kavuri and Milne (2019) highlight the lack of comparative evidence on the types of activities (products and services) of FinTechs.

The objective of this paper is to determine the differences in business model attributes of FinTechs in five rapidly emerging FinTech hotspots in Central and Eastern Europe (CEE). The focus is on Estonia, Latvia, Lithuania, Poland, and Russia because they are in the lead in the CEE region in terms of count of FinTechs[1] (Haddad and Hornuf, 2019; Laidroo and Avarmaa, 2020; Raiffeisen Bank International AG, 2018). The increasing global significance of the selected countries is also reflected in the FinTech city rankings with Vilnius, Warsaw, Moscow, and St. Petersburg being mentioned amongst the nine emerging European

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[1] The same indicators in the Czech Republic and Ukraine also exhibit a rather comparable level of FinTech activity (their position compared to the selected countries varies depending on the information source). However, all other CEE countries remain far behind. Estonia, Latvia, and Lithuania also lead the way in CEE based on counts adjusted for the size of the labour force (Laidroo and Avarmaa, 2020).

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FinTech hubs (CCAF, 2018).[2] In a more recent global FinTech country ranking by Findexable (2020), the selected five countries occupy positions from 4 (Lithuania) to 49 (Latvia)[3], while Lithuania and Estonia are ahead of many of the highly developed Western European countries (e.g., Germany 11th, France 16th, Denmark 20th, Luxembourg 23rd). Although FinTech activity in these countries has rapidly increased, to the knowledge of the authors, no previous study has thoroughly investigated the characteristics of FinTechs in any of the five countries. Even in broader European or global contexts, there exist no in-depth investigations of business models of FinTechs in multiple countries simultaneously.[4]

The five countries provide a suitable setting for doing a comparative analysis because of the characteristics of their FinTech environment. They have, in addition to similar post-Soviet past, also common borders with intensive trade, cross-border capital, and labour markets. However, there exist quite significant differences in their size, entrepreneurial activity, information infrastructure, and financial development (as discussed in Section 2.2). This could potentially have a diverse impact on the business models that FinTechs located in respective countries are utilising. Therefore, we aim to answer the following questions. First, what kind of differences and similarities exist in business model attributes of FinTechs, which have emerged in the five countries? Secondly, how similar or different are the business models of individual FinTechs in the selected countries?

This paper is based mainly on data gathered from 199 FinTechs, which are registered in the five countries and responded to an online survey carried out during February 2019 and January 2020. The survey questions were designed based on Osterwalder and Pigneur (2010) business model canvas and FinTech business model attributes of Lee and Teo (2015) to gather information about their key activities, key resources, value proposition, customer segments, delivery channel, and financial viability. The results were analysed using descriptive statistics and cluster analysis for detecting differences and similarities in business models.

The results show that the main activities of FinTechs in the selected countries vary significantly and are strongly influenced by the maturity of the FinTech market. This leads to differences in resource needs, with a high concentration of small FinTechs (less than 10 employees) in Estonia and Poland, and large FinTechs (more than 250 employees) in Latvia. Also, customer orientation is different, from business-to-business (B2B) services in Estonia and Poland, towards business-to-consumer (B2C) services in Latvia. FinTechs from smaller countries (Estonia, Lithuania, Latvia) are more focused on international customers than in bigger countries (Poland and Russia). In terms of service delivery channels, FinTechs from different countries are rather similar, except Latvia, where physical delivery is as popular as digital delivery. Cluster analysis based on Osterwalder and Pigneur (2010) framework revealed that the FinTechs in the five countries can be divided into four clusters: “lending community”, “mixed services”, “payment service”, and “payment community”. Some of these clusters exhibited characteristics very similar to archetypes reported by Eickhoff et al. (2017). Still, we did observe greater diversity of FinTech business models in Russia and Estonia, the least diverse in Poland. This confirms the cross-country differences in FinTech business models observed also while looking at business model attributes of specific FinTechs. Some of these differences can be linked with differences in local conditions. Therefore, improved understanding of these conditions and FinTech business models would benefit both policy-makers and entrepreneurs.

We contribute to the FinTech literature in several respects. First, we extend the literature of FinTech business models by linking the FinTech taxonomies created in the previous studies by Eickhoff et al. (2017) and Iman (2020) with traditional Osterwalder and Pigneur (2010) business model canvas dimensions. Second, to the knowledge of the authors, it is the first paper, which provides in-depth comparative evidence on the FinTech business models of companies located in several countries. Third, it is the first study investigating FinTech activity in the broader set of CEE countries, which are at the forefront of the European FinTech market.

The paper is divided as follows. The theoretical and empirical background is provided in Section 2. Section 3 focuses on the data and methodology. Section 4 concentrates on the results and discussion and, finally, Section 5 concludes.

2. Business model framework and regional context

2.1. Activities and business models of FinTechs

The main challenge in classifying FinTechs arises from the diverse nature of their activities and the rapid development of the field. Although no universal classification system exists (Iman, 2020), different policymakers have attempted to create their classification systems for dealing with the growing FinTech market (Rupeika-Apoga and Thalassinos, 2020). As can be seen from Table 1, the classifications of policymakers exhibit greater similarity with traditional financial services like payments, insurance, deposits and lending, investment management. Greater variability can be observed in the context of different support services related to analytics, cloud computing, digital identity, cybersecurity, and applications of blockchain or distributed ledger technology.

In line with previous categorisations, we distinguish seven activities of FinTechs: payments, deposit and lending, insurance, investment management, analytics, distributed ledger technology, and banking infrastructure. Payments refer to technology-facilitated payment services like online and mobile payments, integrated billing. Deposit and lending include platform-based financing services cover crowdfunding, peer-to-peer lending, consumer financing, leasing, factoring, and microlending. Insurance refers to technology-enabled insurance services (brokerage and underwriting) often termed as InsurTech. Investment management covers robo-advice, automated advice, social trading, technology-enabled brokerage, and clearing. In defining the last three categories we rely on the definitions employed in Ankenbrand et al. (2019) with analytics covering big data, machine learning, artificial intelligence; banking infrastructure covering user interface, processing enhancement (compliance, identity, and security) and infrastructure technology (open banking); and distributed ledger technology focussing on blockchain-enabled financial services (including digital currency).

Difficulties in classifying FinTechs relate to the emergence of new business models for the provision of financial services. The literature review by Wirtz et al. (2016) concludes that the business model should capture the relevant activities of a company, how it creates value-added, and how this value creation evolves. This indicates that the business model is a wider and more complex phenomenon than just the main activity of the company.[5] Osterwalder and Pigneur (2010) business model canvas is built around nine blocks: key activities, key partnerships, key resources, value propositions, customer relationships,

[2] The remaining emerging hubs are Frankfurt, Barcelona, Milan, Geneva, Brussels, and Istanbul.

[3] Estonia is on the 10th, Poland on the 29th and Russia on the 32nd position.

[4] There do exist numerous country-specific reports that tend to focus on some selected business model aspects.

[5] There exist some papers on FinTech which treat the activity of the FinTech equivalent to their business model. For example, Lee and Shin (2018) identify six business models for FinTech start-ups including payment, wealth management, crowdfunding, lending, capital market, and insurance services. Liu et al. (2020) distinguish nine FinTech business models: online lending, crowdfunding/crowdinvesting, transaction and payment terminals, personal finance management, digital currency, mobile point of sale, robo-advisors, e-banking, and InsurTech.

Table 1
Overview of FinTech classifications.

Financial Stability Board (2017)	World Economic Forum (2015)	International Organisation of Securities Commissions (2017)	Ehrentraud et al. (2020)	In this paper
Payments, clearing and settlement	Payments	Payments	Payments, clearing, settlement	Payments
Deposits, lending and capital raising	Deposits and lending/ Capital raising	Lending/crowdfunding	Deposit and lending/ Capital-raising	Deposit and Lending
Insurance	Insurance	Insurance	Insurance	Insurance
Investment management	Investment management	Trading and investments/Planning (personal finance)	Asset management	Investment Management
Market support (cloud computing applications)	Market provisioning (machine learning, big data)	Data and analytics	–	Analytics
–	–	Security (digital identity, cybersecurity)	–	Banking infrastructure
–	–	Blockchain	Cryptoassets	Distributed ledger technology

Source: Synthesis by the authors based on Financial Stability Board (2017), World Economic Forum (2015), International Organisation of Securities Commissions (2017), Ehrentraud et al. (2020).

channels, customer segments, cost structure, and revenue streams. These blocks can be grouped onto a business model canvas under four main areas of business: infrastructure, offer, customers, and financial viability. According to Wirtz et al. (2016), the business model framework by Osterwalder and Pigneur (2010) is one of the most comprehensive ones covering seven of the potential nine business model components found in the business model literature, falling short only in the aspect of strategy and procurement. For this reason, the business model canvas has gained significant popularity in practice and empirical research (e.g., Sinkovics et al., 2014; Foà, 2019; Specht and Madlener, 2019; Jocevski et al., 2020).

The application of Osterwalder and Pigneur (2010) business model canvas for FinTech business models may require some adjustments (see Table 2). Eickhoff et al. (2017) use a method proposed by Nickerson et al. (2013) and reach a FinTech taxonomy based on six dimensions: dominant technology, value proposition, delivery channel, customers, revenue streams, and product/service offering. All of these components, except for dominant technology, are very similar to the original Osterwalder and Pigneur (2010) dimensions. The review by Clauss (2017) indicates that technology is often viewed as an external factor that affects business model innovations but is not part of the business model. Still, for example, Johnson et al. (2008) consider technology as part of the key resources of the firm. We believe that the dominant technology captures the technological resources needed for the provision of FinTech service, therefore, we link this dimension with the key resources in Osterwalder and Pigneur (2010) framework.

Table 2
Overview of FinTech business model components.

Business model component	Osterwalder and Pigneur (2010)	Eickhoff et al. (2017)	Iman (2020)	Variable used in this paper for analysis
Infrastructure	Key activities	Product/ service offering	Subsector	*activity* (as classified in Table 1) *time use*
	Key partnerships	–	Key actors (suppliers, competitors, complementors)	–
	Key resources	Dominant technology component	Underlying technologies	*employees local employees employment trend dominant technology*
Offer	Value propositions	Value proposition	–	*value proposition*
Customers	Customer relationships	–	–	–
	Channels	Delivery channel	–	*channel*
	Customer segments	Customers	Relationship with the customer; Key actors (customers)	*customer type geographic segmentation*
Financial viability	Cost structure	–	–	*fixed costs to assets*
	Revenue streams	Revenue stream	–	*revenue model*
Other	–	–	Contexts	–
	–	–	Industries	–

Source: Synthesis by the authors based on Osterwalder and Pigneur (2010), Eickhoff et al. (2017), and Iman (2020).

A literature review by Iman (2020) uncovers seven taxonomies of FinTech including the relationship with the customer, key actors, service offered, subsector, underlying technologies, contexts, and industries. As can be seen from Table 2, these dimensions can be linked to many of the dimensions in Osterwalder and Pigneur (2010). Similar to Eickhoff et al. (2017), Iman (2020) adds the technology dimension, which could proxy for some of the key resources of the firm, as explained above. However, there are some exceptions. First, the category "key actors" contains a mixture of aspects from "key partnerships" and "customer segments" in Osterwalder and Pigneur (2010). Second, contexts and industries diverge significantly from the Osterwalder and Pigneur (2010) business model canvas elements, covering developed countries, developing countries, and least developed countries, and industries referring to the financial services industry, IT industry, start-up.

The variables that we will use in our analysis of FinTech business models are presented in the last column of Table 2. With these, we capture most of the original dimensions of Osterwalder and Pigneur (2010) except for customer relationships, which was not covered also by Eickhoff et al (2017).[6] We acknowledge that, in addition to FinTech taxonomies discussed above, alternative approaches have been proposed for example in Gozman et al. (2018) and Gimpel et al. (2018). However, the former remains too simplified in comparison to Osterwalder and Pigneur (2010) setup and the latter too broad to be empirically implementable on a larger dataset. Also, both approaches have been designed based on start-ups only, which may limit their applicability to datasets containing established firms. We also acknowledge that some authors consider technology and service relationship (in our context customers) separately from the business model in e-commerce (Yoo and Jang, 2019).

To provide an alternative perspective to FinTech business models, we

[6] We did initially consider the "key partnership" dimension, however, as less than 50% of respondents provided input and this dimension is difficult to quantify, we left that dimension aside.

do consider in this paper, in addition to the business model framework of Osterwalder and Pigneur (2010), also the five FinTech business model attributes proposed by Lee and Teo (2015). These include low profit margin, asset-light, scalable, innovative, and easy compliance. More details about our operationalisation of FinTech business model attributes are provided in Section 3.

2.2. Attributes of the FinTech environment in the selected countries

Different external country- and activity-specific factors influence the development of business models (Clauss, 2017). To provide an overview of the FinTech environment in the selected countries, in comparison to the European average, we summarize some relevant quantifiable attributes in Table 3.As can be seen from Table 3, there exist very significant differences in the size of the selected countries. The population of Russia is 24 times larger than the total population of Estonia, Latvia, and Lithuania added together and 4 times larger than the population of Poland. When considering the GDP, the differences decrease, however, the ordering of countries remains the same as in the case of population. Yet, once GDP is corrected for the size of the population, the ordering of countries reverses with Estonia and Lithuania being in the lead, followed by Latvia, Poland, and Russia.

Different indicators can be used for capturing the quality of the business environment. One of the more complex indicators is the global competitiveness index developed by the World Economic Forum. Based on that indicator Estonia is in the lead, followed by Russia, Poland, Lithuania, and Latvia. In all of the countries (except for Estonia) the overall competitiveness level remains below the EU average.

As quite a significant portion of FinTech activity is entrepreneurial, one could also consider some kind of combined indicator capturing the quality of the entrepreneurial environment. Stam (2018) proposes an indicator for entrepreneurial ecosystems composed of 10 elements: formal institutions, entrepreneurship culture, physical infrastructure, demand, networks, leadership, talent, finance, new knowledge, and intermediate services. As Stam (2018) applied it to compare the ecosystems of provinces in the Netherlands, we modified the initial proxies, according to data available on the country level, and calculated the entrepreneurial ecosystem index using data on all European countries.[7] As can be seen from Table 3, Estonia has the best additive entrepreneurial ecosystem score of 12.49, followed by Latvia, Russia, Lithuania, and Poland. Estonia's overwhelming superiority arises mainly from the entrepreneurship culture – Estonia has nearly three times greater new business formation than in all other countries. This is further supported by more developed formal institutions. As Poland appears rather far from the remaining four countries and also below the EU average, it does raise the question why Warsaw is viewed as an emerging FinTechs hub (e.g., CCAF, 2018). One potential explanation is that the FinTech ecosystem is a bit different from the traditional entrepreneurial ecosystem.

Considering the peculiarities of the activities of FinTechs, we decided to modify the ecosystem index by Stam (2018). As FinTech relies on the availability and use of information technology and not on the transportation infrastructure, we replaced the infrastructure variables. We also added the overall level of financial development and financial sector regulations as additional FinTech ecosystem elements. Our modified FinTech ecosystem index shows rather interesting developments with Estonia remaining in the lead (score 14.73), followed by Poland, Lithuania, Latvia, and Russia. It is also noteworthy that, except for Russia, the remaining four countries score higher than the EU average. This could explain why the FinTech activity in these countries has been reportedly more active than in many of the more developed European countries.

The discussion above indicates that there exist some differences in the entrepreneurial environment for FinTech companies in the selected countries depending on the types of attributes considered. This refers to the possibility that the business models adopted by FinTechs could also differ across the selected countries. We investigate this aspect in the following sub-sections.

3. Data and methodology

As we needed data on FinTechs, we began with the identification of the FinTech population in each country. We defined FinTechs as companies that contribute to the provision of financial services and have a clear, and generally innovative, information technology component in their business model.[8] To find companies falling under this definition, we started with companies listed as FinTechs in Crunchbase and rechecked whether these companies fell under our definition. Then we added FinTechs found from other data sources that varied across countries, including for example Funderbeam, local FinTech associations (e.g. FinanceEstonia), local central banks, expert knowledge of our commercial partners[9] and checked some existing public lists of FinTechs[10]. We included only those companies that were registered in the analysed countries. The final population of FinTechs contained 670 companies: 232 from Poland, 199 from Russia, 90 from Lithuania, 65 from Latvia, and 84 from Estonia. Based on the company descriptions available on their webpage, we then categorised all FinTechs according to the main field of activity (as classified in Table 1).

3.1. The survey

Most of the data on FinTech business models was collected through an online survey. The survey questionnaire was built around 13 questions similar to the ones previously employed in Ankenbrand et al. (2019). The questions covered the Osterwalder and Pigneur (2010) business model canvas components to identify the variables listed in the last column of Table 2. Key activities were identified by two variables. First, as variable *activity* following the classification in Table 1. Second, managers were also asked to determine on which activities they spend most of their time (*time use*), including programming, marketing, or running daily business. For both of these questions, several options could be selected.

Key resources were proxied with three variables. First, by asking the respondents to present the number of their employees (variable *employees*). Second, by indicating the proportion of local employees in their company (variable *local employees*). Third, the respondents were asked to present their view on the coming year's *employment trend* by selecting one option from the following: large growth, moderate growth, no growth, moderate decline, large decline.

Questions concerning customers concentrated on three variables. These included the variable *customer type* selected as either B2B, B2C, or both B2B and B2C. Variable customer *geographic segmentation* as one of the three: local, international, or both. The variable *channel* was based on the selection of service delivery channels being either digital, personal, or both.

Revenue streams were determined through a single variable *revenue model*. Multiple options could be selected amongst the following: interest income, commission income, license fee, centralized hosting of

[7] In the process, we did omit leadership due to lack of country-based proxies.

[8] This definition is very similar to the one used by Milian et al. (2019).

[9] In the case of Poland, the survey was run by commercial company Quantify in cooperation with QuantFin foundation.

[10] We considered lists provided by Key Capital for Estonia (https://www.keycapital.eu/fintechcompaniesinestonia), Lithuania (https://www.keycapital.eu/fintechcompaniesinlithuania), and Latvia (https://www.keycapital.eu/fintechcompaniesinlatvia); RusBase for Russia (https://rb.ru/fintech/), LAFPA (https://www.lafpa.lv/en/about-us/members/) and LIAA (http://www.liaa.gov.lv/en/invest-latvia/start-up-ecosystem) for Latvia.

Table 3
Attributes of FinTech environment.

Stam (2018) element	Indicator	Data source	Estonia	Latvia	Lithuania	Poland	Russia	Median (5 countries)	Mean EU
–	Population (million)	World Bank	1.32	1.93	2.80	37.97	144.48	2.80	20.71
–	GDP (billion USD)	World Bank	30.73	34.41	53.43	585.66	1657.55	53.43	555.28
–	GDP per capita, PPP (th USD)	World Bank	23.27	17.86	19.15	15.42	11.29	17.86	28.75
–	Global competitiveness index (1 to 7 best)	GCI	4.85	4.40	4.58	4.59	4.64	4.59	4.70
Formal institutions	Corruption perceptions index (0 to 100 best)	Teorell et al. (2020)	70.00	59.00	57.00	62.00	29.00	59.00	57.51
	Rule of law (0 to 16 best)	Freedom House	14.00	12.00	12.00	11.00	2.00	12.00	11.24
	Government effectiveness (0 to 5 best)	Teorell et al. (2020)	3.59	3.57	3.51	3.21	2.30	3.51	3.28
	Voice and accountability (0 to 5 best)	Teorell et al. (2020)	3.71	3.50	3.34	3.34	1.37	3.34	3.18
Entrepreneurship culture	New business registrations per 1000 people ages 15–64	World Bank	23.59	8.01	3.33	1.44	3.26	3.33	5.68
Physical infrastructure	Road connectivity index (1 to 100 best)	GCI	78.00	81.60	84.60	78.70	78.00	78.70	73.50
	Efficiency of seaport services (1 to 7 best)	GCI	5.60	4.80	4.60	4.40	4.60	4.60	4.45
	Efficiency of train services (1 to 7 best)	GCI	4.70	4.50	4.50	4.00	4.90	4.50	4.05
	Efficiency of air transport services (1 to 7 best)	GCI	4.60	5.50	4.60	4.80	4.90	4.80	5.00
Demand	Market size (1 to 100 best)	GCI	42.30	44.00	50.10	73.40	84.00	50.10	58.52
Networks	Multi-stakeholder collaboration (1 to 7 best)	GCI	4.00	3.50	4.10	3.10	4.00	4.00	4.01
Talent	Tertiary education enrollment gross %	World Bank	69.55	67.04	68.53	68.11	80.39	68.53	66.89
Finance	Financing of SMEs (1 to 7 best)	GCI	4.40	3.40	3.70	3.90	3.30	3.70	3.95
New knowledge	R&D expenditures as % GDP	GCI	1.50	0.60	1.00	1.00	1.10	1.00	1.38
Intermediate services	Competition in services (1 to 7 best)	GCI	5.70	5.40	5.40	4.90	5.40	5.40	5.20
	Additive entrepreneurial ecosystem index	Calculation, authors	**12.49**	**8.54**	**8.29**	**7.98**	**8.40**	**8.40**	**9.00**
IT infrastructure	IT infrastructure indicator (1 to 7 best)	GITR	6.50	5.00	4.50	5.30	4.70	5.00	5.45
Additional demand indicator	Used a mobile phone or the internet to access an account (% age 15 +)	World Bank	74.82	60.75	55.89	64.60	39.57	60.75	48.99
Financial regulations	Presence of FinTech regulations (1 to 5 best)	Authors	2.00	2.00	3.00	3.00	1.00	2.00	1.88
Financial development	Financial development index (0 to 1 best)	IMF	0.33	0.28	0.26	0.48	0.48	0.33	0.48
	Additive FinTech ecosystem index	Calculation, authors	**14.73**	**10.25**	**10.34**	**10.57**	**9.42**	**10.07**	**9.51**

Source: compiled by authors, GCI refers to the Global Competitiveness Report, GITR to Global Information Technology Report by the World Economic Forum.

business applications, trading income, data, advertising income, or other.

To get a deeper insight into the business model components, we also added six questions to cover the business model aspects of Lee and Teo (2015). Respondents were asked to evaluate their company against competitors based on profit margin, fixed costs to assets, ability to scale, innovativeness, ease of compliance, and costs to customers. The evaluation scale ranged from 1 (very low) to 7 (very high).

Additional questions (outside of the business model focus) covered the operations of the companies including revenue and funding indicators, and maturity of the company (either already running, under construction, or developing). We also asked the respondents to evaluate their sentiment towards competition, finding customers, access to finance, costs of labour, staff, regulation, and expansion to international markets (measured on the scale from 1 – not pressing to 10 extremely pressing). As the purpose of the survey was also to provide input for local stakeholders, FinTechs were asked to indicate their outlook on the prospects of the sector and factors inhibiting its development.

The survey was carried out in Estonia, Latvia, Lithuania, Poland, and Russia from February 2019 to January 2020. The average survey period was three months and it varied across countries. GoogleDocs was used as the main survey platform. In Poland, it was eventually replaced with a professional survey platform provided by the commercial partner Quantify, who ran the survey because the initial attempts led to only 6 responses. Links to the online questionnaire were sent by e-mail to all companies identified as FinTechs (while in Poland a large part of the survey was performed also by telephone interview). Suitable e-mails were determined based on data presented in local business registries, companies' web-pages, or found through personal contacts. If possible, the e-mail was targeted directly to the company's owners, board members, or executives (e.g., CEO, CFO). In remaining cases, it was sent to the company's general e-mail. The first e-mail was followed by two to three reminders. In some cases, also follow-up phone calls and instant messaging through social media were used to increase the response rate. Local institutions helped also by spreading the word about the survey and news sites were used for the same purpose. Despite different measures taken, we got in a total of 199 responses. The response rate remained on average 27%: 38% in Estonia, 36% in Russia, 32% in Latvia and Lithuania, and 19% in Poland. Representativeness of the sample was tested using Pearson's Chi2 test on the proportions of activities in the surveyed FinTechs in comparison to the population. These statistics with their associated *p*-values are presented in Panel C in Table 4 for all countries together and also for each country separately. The responses are representative for the whole region, less so for Estonia and Latvia individually. As we are focused more on the whole region, the potential bias remains low.

3.2. Modifications to the dataset and cluster analysis

Before the analysis, we made some modifications to the dataset. First, the respondents provided their view of their main activity. As they could select multiple activity types, we needed to narrow it down to the single main activity. Therefore, we used the input from respondents to check the appropriateness of our initial FinTech activity classifications. At least two persons checked the consistency of categorizations and differences in opinion were discussed. Still, it is important to note, that the definition of the main field of activity remains arbitrary.

Second, the survey did not properly cover some business model

Table 4
Distribution of population and final sample by type of FinTech activity.

Panel A. Population (670 companies)	Estonia	Latvia	Lithuania	Poland	Russia	Total
Analytics	4%	5%	0%	9%	12%	8%
Banking infrastructure	17%	15%	27%	19%	20%	20%
Deposit & lending	29%	48%	10%	24%	27%	26%
Distributed ledger technology	32%	9%	9%	5%	4%	9%
Insurance	4%	0%	1%	4%	0%	2%
Investment management	0%	9%	3%	10%	10%	8%
Payment	15%	14%	50%	30%	27%	28%
Total	100%	100%	100%	100%	100%	100%
Total number of FinTechs	84	65	90	232	199	670
Panel B. Final sample (199 companies)	Estonia	Latvia	Lithuania	Poland	Russia	Total
Analytics	9%	10%	0%	11%	11%	9%
Banking infrastructure	16%	0%	34%	20%	24%	21%
Deposit & lending	22%	62%	14%	22%	33%	29%
Distributed ledger technology	22%	0%	7%	2%	1%	6%
Insurance	6%	0%	0%	2%	0%	2%
Investment management	0%	10%	3%	7%	11%	7%
Payment	25%	19%	41%	36%	19%	27%
Total	100%	100%	100%	100%	100%	100%
Total number of FinTechs	32	21	29	45	72	199
Panel C. Tests of representativeness	Estonia	Latvia	Lithuania	Poland	Russia	Total
Pearson Chi2	11.48	11.18	2.90	2.94	6.41	6.46
Pearson Chi2 p-value	0.04	0.05	0.72	0.82	0.27	0.37

Source: compiled by authors.

components like the value proposition[11] and dominant technology. Also, the delivery channel classification was very simple. Therefore, we decided to generate three additional variables for these business model components following the taxonomy presented in Eickhoff et al. (2017). The *value proposition* variable covers automation, collaboration, customisation, insight, intermediation, monetary, financial risk, transparency, consolidation, security, and usability. *Dominant technology* covers blockchain, digital platform, decision support system, marketplace, database system, and transaction processing system. An alternative classification for *delivery channel* covers application programming interface (API), mobile application, physical connection, web application, web application together with the mobile application, and instant message. The missing data for the respondents was backfilled by two persons using public information sources (mainly company web-page and data provided by respondents in a more descriptive format in the survey). One person generated the classifications for all FinTechs in the sample and then the classifications were checked by another person. At least one of these persons had very good local knowledge.

As the dataset contains a lot of information, we try to reduce the number of tables presented in the main body of the paper. The dataset is available from Mendeley Data (Laidroo et al., 2020).[12] To provide a reader with a possibility to look deeper into the numbers, which are mentioned in the descriptive analysis in Section 4.1, we have created Online Appendices which are part of the data repository file. In this paper, we will not refer to the figures contained in the Online Appendix to maintain better readability. However, the online appendices contain references to relevant sections of the paper.

The survey and backfilling of data provide a dataset containing all business model characteristics previously listed in the last column of Table 2 for each respondent. This data was analysed first using descriptive statistics. Previous studies developing FinTech taxonomies (e.g., Eickhoff et al., 2017; Gimpel et al., 2018; Gozman et al., 2018) have employed cluster analysis similarly to studies focusing on taxonomies of business models (e.g., Täuscher and Laudien, 2018; Camisón and Villar-López, 2010; Urban et al., 2018). Therefore, we also decided to use partition-based clustering for determining the groups of more similar FinTechs based on their business models using the following R packages: cluster (Maechler et al., 2019) and skmeans (Hornik et al., 2012). We preferred partition-based clustering over hierarchical clustering because non-hierarchical methods have been considered superior over hierarchical ones in management-based research (for discussion see Ketchen and Shook, 1996). Therefore, our baseline results reported in Section 4 will rely on partition-based clustering.

The standard method for non-hierarchical clustering is the k-means algorithm in which the objects are partitioned in such a way that the Euclidean distance between the cluster centre (centroid) and the members of the cluster are minimized. In other words, each observation belongs to the cluster with the nearest mean. The method has been further modified and extended. One possible modification is to use the median instead of the mean. In this case, we talk about the partitioning of the data into k clusters "around medoids" (so-called PAM algorithm), which is a more robust version of k-means algorithm. In the first step of the PAM method, the algorithm searches for the k representative objects (or medoids). Next, each observation is assigned to the nearest medoid and the k clusters are constructed. The goal of the algorithm is to find k representative objects, which would minimize the sum of the dissimilarities of the observations to their closest representative object (see Reynolds et al, 1992; Struyf et al., 1997 or Schubert and Rousseeuw, 2019 for details).

The main problem in the partition-based clustering algorithms is to find the optimal number of clusters. We applied two approaches. The first is based on minimizing the within-cluster sum of squares – hereafter WSS (so-called *elbow method*). The idea of the elbow method is to minimize the total intra-cluster variation, measured by the WSS. It treats the total WSS as a function of the number of clusters. The number of clusters should be chosen in such a way that adding another cluster does not improve the total WSS much. The curve of WSS against the number of clusters is plotted and the location of a bend (knee) is considered as an appropriate number of clusters.

[11] The value proposition was covered in the survey in four countries of the five. However, the response was provided as a description and these descriptions remained hard to classify.

[12] Interested readers can find more about the FinTech environment and FinTechs in selected countries in reports prepared for Poland (Kliber et al., 2020), Latvia (Rupeika-Apoga et al., 2020) and Estonia (Tirmaste et al., 2019). In the Polish report, a slightly modified definition of FinTech is used compared to the one used in this paper.

An alternative approach is based on maximizing the average silhouette (Kaufman and Rousseeuw, 1990). It computes the average silhouette of observations for different values of k. The optimal number of clusters is the one that maximizes the average silhouette over a range of possible values of k. The silhouette analysis itself measures how well an observation is clustered and it estimates the average distance between clusters. The silhouette plot displays a measure of how close each point in one cluster is to points in the neighbouring clusters.

The silhouette value $s(i)$of the object i can take any value from the interval $<-1;1>$ and:

- if $s(i)$ is close to 1, the object i is well classified (in cluster A),
- if $s(i)$ is close to 0, the object i can either belong to cluster A or B,
- if $s(i)$ is close to -1, the object is badly classified (closer to B than to A).

Struyf et al. (1997) suggest the following interpretation: if $0.71 \leq s(i) \leq 1$, the strong structure has been found, if $0.51 \leq s(i) \leq 0.7$ – the classification is called reasonable.

When using PAM algorithm on the Osterwalder and Pigneur (2010) classification, we proxied key activities with *activity*. We disregarded the alternative key activity indicator *time use* as it did not seem to exhibit distinctive variation across clusters in the first round of cluster analysis. Key resources were proxied with three variables: *employees*, *local employees*, and *dominant technology*. Indicator *employment trend* was left aside as the other indicators concerning employees are more objective. Value propositions were represented by the variable *value proposition*. Customers were proxied with three variables: *delivery channel*, *customer type*, and customer *geographical segmentation*. We disregarded the simpler indicator for the delivery channel (*channel*) as it did not seem to exhibit distinctive variation across clusters in the first round of cluster analysis. The cost structure was proxied by *fixed costs to assets*. Revenue stream was represented with the *revenue model*. As the data for all selected variables was not available, the final sample for Osterwalder and Pigneur (2010) classification drops to 192 FinTechs. The silhouette measure for the different number of clusters together with the size of the cluster is presented in Appendix 3. The average silhouette width was maximized for the two clusters containing 42 and 150 FinTechs. With three and four clusters, the average silhouette was almost equal, however, the individual silhouette for cluster 1 in the three cluster case (0.416) remained too small to be acceptable. In the 5-cluster case, the individual silhouette of Cluster 1 and 3 was too small to be acceptable. As in the 4-cluster case the silhouette exceeded 0.5 in each individual case and we considered that it would give us more insight in the data (compared to the best 2-cluster case), we decided to use four clusters.

To check the robustness of the results, we compared the results of partition-based clustering with the results of the hierarchical clustering through the value of the silhouette. The results of hierarchical clustering on Osterwalder and Pigneur (2010) dimensions using single, complete, and centroid linkage are presented in Appendix 4. As can be seen from Appendix 4, the average silhouette obtained with complete and centroid linkage is similar to that obtained with PAM. When we compare the clusters obtained with PAM and hierarchical methods, we observe that the clusters remain similar, especially with the centroid linkage method. This indicates that the classification obtained with PAM is rather robust. We tried also a robustness test with the mixture-model clustering[13], however, this algorithm used to end up in local maxima despite trying the same or different starting points, giving unstable and, hence, rather unreliable results (see the discussion on the pros and cons of using different types of clustering algorithms for instance in Nerurkar et al., 2018 or Jung et al., 2014). As in the case of mixture-model clustering the silhouette values for any number of clusters from 2 to 5 were also much lower (below 0.4) than the ones obtained for the hierarchical and partition-based methods, we will not report these in the paper.

In the case of the Lee and Teo (2015) model, we use the spherical k-means partition, in which all vectors are normalized, and distance measure is cosine dissimilarity – for details see Dhillon and Modha (2001). We used the following five types of variables: profit margin, asset-light (the fixed cost to assets), ability to scale, innovativeness and ease of compliance. Each of the variables took value from 1 to 7. As the data for all selected variables was not available, the final sample with Lee and Teo (2015) model drops to 197 FinTechs. The best results in terms of the silhouette measure were obtained for spherical k-means algorithm and two clusters. Still, we acknowledge that the average silhouette value (0.51) is on the verge of acceptable value. In addition to spherical k-means algorithm, we tried, as a robustness test, also hierarchical partitions using cosine distance matrix and Euclidean dissimilarity matrix with 2 clusters. As can be seen from Appendix 5, the average silhouette was maximised for single/centroid partition of cosine dissimilarity. However, the size of clusters (2 and 195) was not desirable for our purposes and the other methods were outperformed by the spherical k-means. This indicates that k-means provides the best classification based on Lee and Teo (2015), however, this classification is significantly harder to replicate compared to the one based on Osterwalder and Pigneur (2010).

4. Results and discussion

4.1. Comparative evidence on the business model attributes of FinTechs

In the following sub-Sections 4.1.1–4.1.5. we will discuss the results concerning the business model dimensions based on Osterwalder and Pigneur (2010). Section 4.1.6. focuses on results based on the business model framework proposed by Lee and Teo (2015).

4.1.1. Key activities

One of the most important characteristics of FinTech is its main activity (variable *activity*). This is the only characteristic for which we have data covering the whole population of 670 FinTechs in Estonia, Latvia, Lithuania, Poland, and Russia.

As can be seen from Panel A in Table 4, over 25% of all FinTechs in the selected countries are involved either in payments (28%) or deposit and lending (26%). As these activities represent the more frequently used financial services, their dominance in the context of FinTech services is not surprising. The least popular activities covering insurance, analytics, and investment management account for less than 12% of FinTechs in all five countries. However, on a country basis, the ordering of the most popular types of activities does vary referring to country-specific drivers' influence on the development of the FinTech market. The most striking difference is related to Estonia, where companies involved in distributed ledger technology applications (32%) dominate the whole FinTech landscape. These types of companies account for less than 10% of the FinTechs in the remaining countries. This result could be partly a reflection of the more developed IT infrastructure and greater demand for digital financial services (see Table 3). On the other hand, the deeper investigation did reveal that many of these companies are foreign-owned, meaning that one of the reasons why they are headquartered in Estonia could also be related to the e-residency, which allows foreigners to set-up companies easily through digital channels. The lower dominance of payments (compared to other countries) could also be explained with very developed digital payment infrastructure within commercial banks, which reduces the need for niche payment services.

[13] We applied a latent class mixture model using fpc package in R (Henning 2020). Since we had in our dataset a mixture of categorical and continuous variables, they were modelled by a mixture of distributions. The categorical variables were modelled within components by independent multinomial distributions, while the continuous one by the Gaussian distribution. The model was fit by maximization of the likelihood function computed with the EM-algorithm. The number of components was chosen using the Bayesian information criterion.

Lithuanian and Latvian FinTech landscape is less balanced than in Poland and Russia with the most popular types of FinTechs (payments and deposit and lending, respectively) accounting for nearly half of the FinTechs. In Latvia, more often than in other Baltic countries, people borrow at times when there is an unforeseen need for additional financial resources, moreover, the majority of such borrowers are young people (Rupeika-Apoga et al., 2020). This tendency explains the popularity of deposit and lending type dominance in Latvia, showing that banks are not interested in providing loans to this group of customers (Rupeika-Apoga and Saksonova, 2018). It is also noteworthy that compared to other countries Lithuania has a stronger presence of banking infrastructure FinTechs (27%). This could reflect the fact that many international banking groups have set up their support activities in Lithuania and this is fuelling the development of services that could potentially decrease the use of workforce. Greater balance of FinTech activities in Poland and Russia could be explained by the significantly greater size of the market which allows easier creation of a critical mass of FinTechs in a given activity area.

As our survey covered only 29.7% of the population, we provide also an overview of the activities of those FinTechs that responded to our survey. The distribution of their activities, presented in Panel B in Table 4, shows that FinTechs involved in payments or deposits and lending dominate also our sample. As the differences in proportions of all FinTech activities of our regional sample in comparison to the population remain between +-3% compared to the population, the representativeness of the whole sample is good. Greater differences in proportions are observed on a country basis, especially for Estonia and Latvia.

The respondents were also asked to classify their business as already running or under construction. 77% of respondents had already passed the construction phase and were already running their businesses. However, there existed rather significant cross-country differences. The most mature FinTechs were in Latvia where all respondents were already running their business. In Russia the share of respondents under construction was almost two times greater than in other countries, reaching 43% of all respondents. This does seem to indicate that the Russian FinTech market is in a more rapid growth phase compared to the other four countries. The distribution of companies in the construction phase across types of activity was very similar to those already running their business. This indicates that the attention of entrepreneurs continues to be rather evenly divided across the types of FinTech activities. The only exception was analytics where 39% of companies were under construction. However, this result was entirely driven by Russian FinTechs.

FinTechs were also asked to indicate which activities they spend most of their time on (variable *time use*). 68% of respondents indicated engagement in programming activities and 61% in running the daily business while only 32% mentioned marketing. Again, a bit more mature companies seemed to dominate the Latvian FinTech market where twice as many respondents (86%) mentioned running daily business compared to those mentioning programming (43%). In all other countries, the programming activity was mentioned more frequently than running daily business. Considering that the proportion of companies under construction is three times lower than the proportion of companies mentioning programming (except for Russia), FinTechs do seem to focus on this activity strongly even when the company becomes more mature. In most types of FinTechs, the effort made for programming and running the daily business were considered equally important. However, in FinTechs focusing on distributed ledger technology, the importance of programming was mentioned by all respondents with other activities being mentioned five times less frequently. This shows that although all FinTech activities require programming efforts, the success of distributed ledger technology FinTechs is more reliant on the application of technology. Rather surprisingly, marketing was mentioned three times less frequently by Russian FinTechs (11% of respondents) compared to FinTechs in the other countries. This could reflect the combined impact of a bigger share of companies under construction and the big domestic market, which could lower the relevance of marketing efforts. When looking at all responses, the popularity of marketing activity was equally relevant for all types of FinTechs with roughly 1/3 of respondents mentioning it.

4.1.2. Key resources

In terms of the number of employees (variable *employees*), 58% of all respondents had 25 or fewer employees and only 13% had more than 100 employees. From the five countries, Poland and Estonia had the greatest proportion of smaller FinTechs with less than 7% of FinTechs having more than 100 employees and over 40% of FinTechs having less than 10 employees. On the other hand, in Latvia, the share of FinTechs with over 250 people is 30% (again leading back to the conclusion of having more mature companies). When looking at the main activity of FinTechs, deposit and lending and investment management FinTechs tended to be bigger with over 20% of FinTechs having over 100 employees and less than 46% of FinTechs having less than 25 employees. These traditional financial services could be dominated by more established companies. However, it is interesting to note that in the context of payments, 68% of FinTechs have less than 25 employees. This seems to indicate that FinTechs involved in payments tend to be smaller companies providing niche products. At the same time, all surveyed FinTechs in distributed ledger technology had less than 50 employees.

It appeared that the Estonian and Latvian FinTechs were the most international with 31% and 24% of their employees being located abroad. In the whole sample, the share of employees abroad was 17% and the lowest share of employees abroad was observed in Poland (5%). The need for foreign labour could be linked to the size of the domestic labour market as well as the international ambition of the company. We will focus more on the internationality aspect when discussing customers and revenues in Section 4.1.4 and Section 4.1.5.

Employment trend was clearly towards increasing employment with 64% of respondents expecting moderate or large growth and only 3% referring to a decline (the remaining 33% expected no changes). The greatest employment growth potential was expected in Lithuania and Estonia where nearly 90% of respondents were expecting to increase their employment. From the types of activity, distributed ledger technology exhibited the most optimistic growth outlook with 89% of respondents referring to employment growth. The latter result seems to reflect the young age of the technology the application of which has great growth potential. As the surveys were conducted before the COVID crisis, it is difficult to estimate how that could affect the future growth potential of FinTechs in the region.

We also determined the *dominant technology* of FinTechs (one or several). The most frequently utilised technologies across all surveyed FinTechs included marketplaces (37%), transaction processing systems (36%), and digital platforms (23%). Marketplace technology dominated in deposit and lending activity, transaction processing systems in payments and digital platforms were used more frequently in banking infrastructure and payment services. Database systems, decision support systems, and blockchain were used in less than 12% of FinTechs and did not play a dominant role in any of the recorded FinTech activities. Still, most of the technologies were detected at least once for five or more FinTech activities (except for blockchain which was observed only in three types of FinTechs). The close connection of the technology with the main activity of the FinTech explains also some striking country-based differences in the popularity of different technologies in Latvia and Estonia compared to other surveyed countries. In Latvia, 62% of surveyed firms used marketplace technologies. In Estonia, marketplace technologies and digital platforms were followed instead by blockchain (recorded for 28% of firms). These results refer to the Latvian market being dominated by deposit and lending FinTechs and the Estonian market exhibiting a stronger presence of FinTechs providing services based on distributed ledger technology.

4.1.3. Value proposition

Instead of narrative descriptions provided by FinTechs in the survey, we determined the value proposition through publicly available data after the survey. The most common type of value proposition was usability which was observed in 56% of surveyed firms and dominated the results in all surveyed countries. The remaining rather equally frequently detected types of value proposition included monetary, intermediation, transparency, automation, and collaboration, being detected in 21 to 26% of surveyed FinTechs. Customisation, security, financial risk, consolidation, and insight were detected in 6 to 15% of cases. No significant differences emerged in the frequencies of the types of value propositions across countries. In terms of the fields of FinTech activity, the value propositions did differ. For example, payments and analytics could be linked to almost all types of value propositions (except for insight) rather equally. The value proposition of deposit and lending FinTechs, on the other hand, was more clearly concentrated around monetary, intermediation, financial risk, and transparency. In banking infrastructure FinTechs, the same value propositions were the least relevant, with more focus being on collaboration, automation, customers, usability, and security.

4.1.4. Customer segments and delivery channel

The respondents were asked to determine their *customer type*. 43% of FinTechs concentrated only on businesses, 26% only on consumers, and the remaining FinTechs on both. Over 53% of FinTechs in Estonia and Poland concentrated only on businesses, while consumers were the main focus of 62% of Latvian respondents and both types by 59% in Lithuania. The most even distribution of customer groups was observed in Russia. Business customers were more common amongst FinTechs focusing on payments and banking infrastructure, while consumers were the dominant customers of deposit and lending FinTechs. Still, even in all of these activity fields, at least some FinTechs reported also other types of main customer groups.

In terms of customer's *geographic segmentation*, 43% of respondents concentrated on international customers and 53% on local customers (the remaining on both). However, the focus of FinTechs located in different countries was very different. 77% of Estonian, 69% of Lithuanian, and 57% of Latvian FinTechs concentrated on international customers. The same indicator in Russia was 26% and in Poland only 22%. As the first three countries are smaller in terms of population and economy, it refers that FinTechs established in smaller countries do seem to have a more ambitious agenda due to the limitations of the domestic market. In Poland and Russia, the vast domestic market provides rather good opportunities to develop their business domestically. However, over the long run, it may hinder the capability of these companies to compete internationally. This conclusion is also supported by the proportion of employees abroad which was greater in smaller countries (see Section 4.1.2) When looking at the main customers of FinTechs involved in different main activities, it appears that the most international focus characterises FinTechs in distributed ledger technology 90% of which concentrate on international customers. 79% of investment management FinTechs focus instead on the domestic market. Both of these results could be partially driven also by country-specific factors as most distributed ledger FinTechs originate from Estonia and most investment management FinTechs from Russia and Poland.

In terms of the delivery channel of their services (variable *channel*), 64% of respondents were using both digital and personal communication, 35% only digital communication, and almost negligent 1% only personal communication. Digital-only communication was a bit less common in Latvia and Poland with shares less than 18%. The greatest proportions of digital-only communications were observed in FinTechs focusing on distributed ledger technology and investment management (60% and 57% respectively). This indicates that digital-only communication is a bit activity-specific. Considering that almost all FinTechs are concentrating on digital communication even if it is mixed with personal communication, the digital literacy of their customers remains a key driver of their success.

We determined the delivery channel also through publicly available data after the survey following a wider set of categories (variable *delivery channel*). The most frequently detected channels for all surveyed FinTechs included web applications (40%), application programming interfaces (28%), and web application together with mobile applications (27%). These delivery channels dominated in all surveyed countries except for Latvia. In Latvia, the physical connection was detected for 90% of FinTechs, at the same time the share of a web application together with the mobile application was also high compared to other countries (48%). This refers that Latvian FinTechs are trying to combine traditional physical delivery with innovative ones and such tendency can be partly explained with the dominance of deposit and lending activity and that all respondents were already running their business. In all other countries, the physical connection was detected in 6 to 18% of FinTechs. Almost negligible relevance was detected for instant messaging which was present only in 2% of FinTechs. In terms of the type of FinTech activity, the most even distribution of delivery channels is observed in payments and analytics across all possible delivery channels (except for instant messaging which remained at modest levels). Deposit and lending activities exhibited a strong reliance on web applications followed closely with a physical connection (as in the case of Latvia) while banking infrastructure FinTechs focused mainly on the delivery through application programming interfaces.

4.1.5. Revenue streams

Revenue of FinTechs may be based on different sources and FinTechs could indicate all models that are relevant for them (variable *revenue model*). The most frequently mentioned sources of revenue of respondents covered commission income (59%), interest income (24%), license fee (21%), and centralised hosting of business applications (21%). Trading income, data, advertising, and other income were mentioned by less than 10% of respondents. While commission income was the most frequently mentioned revenue model in all countries, the relevance of other revenue models varied. For example, interest income was mentioned as the second most frequent model by 62% of respondents from Latvia while in other countries it was mentioned by less than 34% of respondents. Centralized hosting of the business applications was mentioned as the second most frequent in Estonia (by 40% of respondents) and the license fee in Poland (by 47% of respondents). Revenue sources tended to vary depending on the main activity of the FinTech. In our sample, the commission income was the most common amongst payment, deposit and lending, and investment management and distributed ledger technology FinTechs. It very clearly dominated other revenue sources in payments, however, in deposit and lending it was almost as relevant as the interest income. FinTechs involved in analytics relied more on income from data and banking infrastructure FinTechs on income from centralized hosting of business applications. As revenue structure is easier to analyse in the context of the whole business model, we will turn to this issue in Section 4.2.

4.1.6. Evaluation of Lee and Teo (2015) business model dimensions

The mean evaluations of business model components suggested by Lee and Teo (2015) by countries are mapped in Fig. 1. Lee and Teo (2015) suggest that successful FinTechs should have a low profit margin and low fixed costs to assets. The lowest profitability was observed in Poland, while the highest in Latvia. The level of fixed costs to asset ratio puts Estonian FinTechs into a better position and Lithuanian FinTechs in the worst position. The remaining dimensions should score higher for more competitive FinTechs. In all three remaining dimensions, Russian FinTechs stand out with very positive results. Better scalability could be explained by the size of the domestic market. However, the Polish scalability indicator remains half of that of the Russian indicator, indicating that perhaps our Russian respondents have been more optimistic or were comparing themselves to less-developed FinTechs. The latter conclusion is partly supported by the innovativeness dimension where

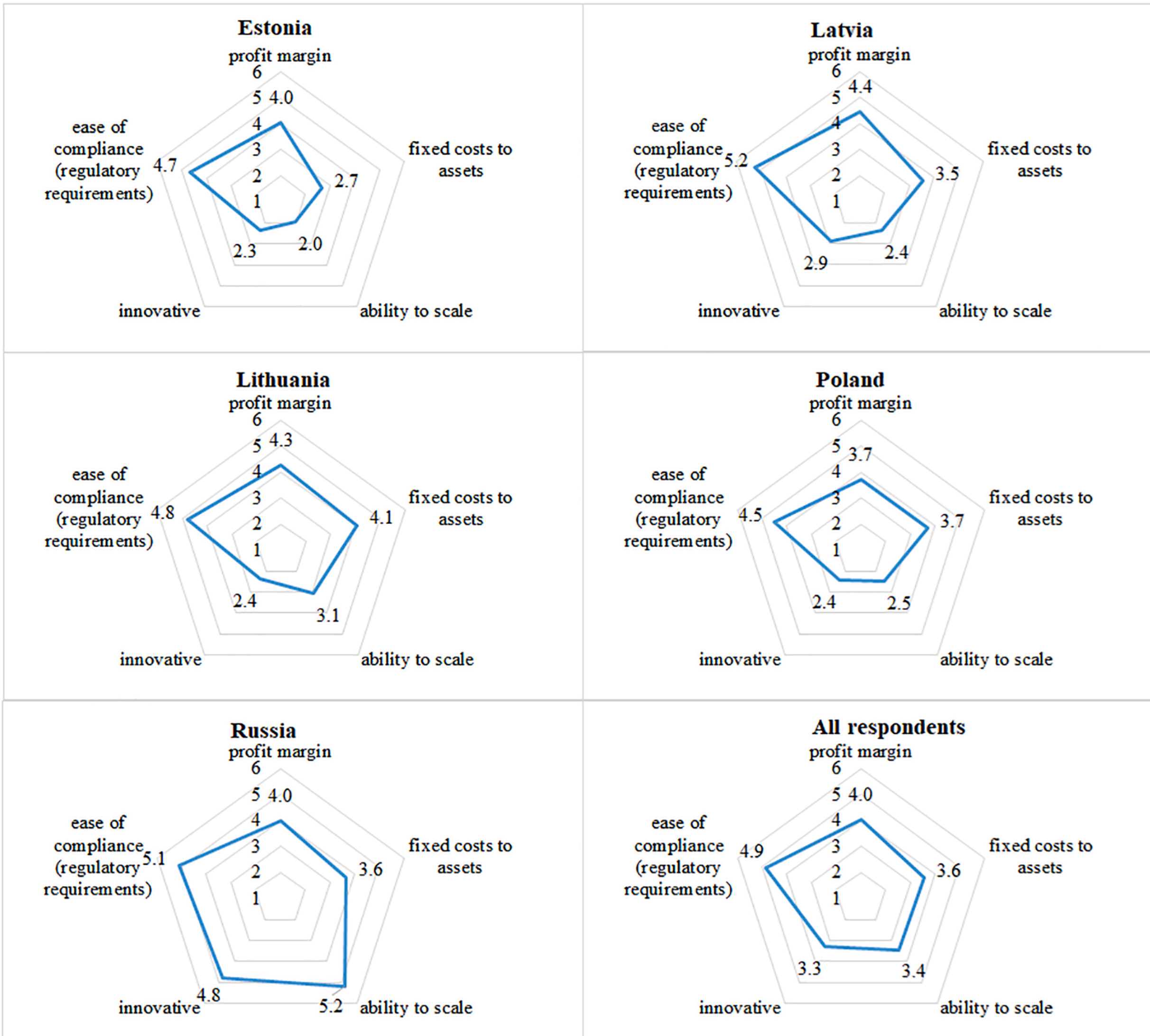

Fig. 1. Mean evaluations of Lee and Teo (2015) business model dimensions by countries Source: compiled by authors.

for example Estonian FinTechs got 2.5 points lower result while there is a very clear dominance of distributed ledger focused FinTechs in that sample.

When trying to rank the FinTechs by countries based on the selected five attributes, we would conclude that the Russian FinTechs are in a significantly more competitive position, followed by Latvia and Poland. Lithuania and Estonia are further behind. Although these rankings are based on a subjective evaluation of a limited number of business model attributes, they do provide an interesting insight into the thinking of managers or FinTechs in the five countries.

We also mapped the five attributes across the main activity of FinTech (instead of the country of registration). As can be seen from Appendix 1, the evaluations vary significantly with distributed ledger technology FinTechs providing rather conservative evaluations to all five attributes. The highest evaluations for profit margins are observed in analytics and lowest in the distributed ledger technology area. This is not too surprising as FinTechs in the latter field are more in the construction phase. The most asset-light companies are also in distributed ledger technologies and the most asset-heavy in deposit and lending. Surprisingly banking infrastructure stands out with the best evaluations for scalability, innovativeness, and ease of compliance. The latter results seem to be partly driven by the very optimistic responses of Russian FinTechs involved in banking infrastructure.

4.2. Similarities and differences in the business models

The cluster analysis based on Osterwalder and Pigneur (2010) business model components led to the distribution of 192 FinTechs into four clusters (see Table 5).[14] Clusters are of very uneven sizes with 132

Table 5
Number of FinTechs by home country within a given cluster.

Country	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total
Estonia	4	11	10	5	30
Latvia	5	1	14	0	20
Lithuania	0	1	22	5	28
Poland	2	0	41	0	43
Russia	5	11	45	10	71
Total number of FinTechs	**16**	**24**	**132**	**20**	**192**

Source: compiled by authors.

[14] We lost seven observations as some respondents skipped the question providing input on some of the business model components.

(69%) FinTechs belonging to cluster 3 and the remaining FinTechs being more evenly distributed between the remaining three clusters.

It is possible to observe that FinTechs from different countries are rather unevenly distributed between the clusters. Cluster 1 has no Lithuanian, cluster 2 no Polish, and cluster 4 no Latvian or Polish FinTechs. In general, Polish FinTechs are mainly in cluster 3 with a very low presence in cluster 1, while Estonian and Russian FinTechs are present in all clusters. This indicates that the diversity of FinTech business models is greater in these two countries. To interpret these results, we need to understand the dominant business model characteristics of FinTechs within the four clusters. Therefore, we calculated for each cluster the proportions of FinTechs within a given Osterwalder and Pigneur (2010) business model category. The detailed percentages by categories are presented in Appendix 2. In Table 6, we summarize the most dominant results by each business model dimension.

We label cluster 1 as a "lending community" (LC). A typical FinTech belonging to the cluster can be characterised as a well-established crowdfunding platform with strong international ambition servicing exclusively either consumers or businesses. In terms of FinTech *activity*, cluster 1 stands out from other clusters by being more focused on fewer FinTech activities. It is dominated by FinTechs involved in the deposit and lending (56%). This also explains why the greatest portion (59%) of FinTechs have *dominant technology* related to a marketplace and their value proposition is, in addition to usability that is important in all clusters, related to intermediation, monetary, and financial risk. Cluster 1 is also characterised by the greatest average size of companies having the largest portion of FinTechs with over 250 employees and the lowest portion with less than 10 employees. It also has the greatest average percentage of employees abroad (12.3%). This indicates that FinTechs in cluster 1 are larger, more established firms with a large international workforce. It is also the only cluster that has the *delivery channel* being dominated by physical contact and web applications, the main *customer type* being B2C with customer *geographic segment* being dominantly international. It is rather striking that the share of FinTechs focusing simultaneously on B2B and B2C services is very low, indicating that the "typical" FinTech in this cluster concentrates only on one customer segment at a time. The *revenue model* of FinTechs in cluster 1 is uniquely being dominated by interest income. This indicates that many of the dominant characteristics of this cluster coincide with lending community archetype in Eickhoff et al. (2017).

We label cluster 2 as "mixed services" (LC + PS + O) because it shares some common traits with cluster 1 by having the most FinTechs also in deposit and lending, however, the banking infrastructure and payments are also quite strongly represented. This creates a situation where FinTechs of all sizes are present, digital platforms arise next to the marketplace as the second most relevant *dominant technology*. 74% of the employees are local. Customer dimension becomes dominated by application programming interfaces (APIs), and web applications, B2B relationships, and greater relevance of local customers. The main *revenue model* is now commission income. This indicates that a typical FinTech in cluster 2 could be characterised as locally focused business-oriented FinTech providing services through APIs for a commission fee. Based on the archetypes in Eickhoff et al. (2017) cluster 2 is a hybrid of lending community, financial markets intermediary, and payment service archetypes.

Cluster 3 and 4 are more similar to each other. We label cluster 3 as "payment service" (PS). Cluster 3 is tilted more towards "true" payment activities with greater use of transaction processing systems, web applications, servicing more frequently businesses and local customers for a commission fee. The workforce in this cluster is almost exclusively local. Therefore, we could characterise a typical FinTech in cluster 3 as users of transaction processing systems for the delivery of mainly payment services to local businesses through web and/or mobile applications. Many of the dominant characteristics of cluster 3 coincide with the payment service archetype in Eickhoff et al. (2017).

We label cluster 4 as a "payment community" (PS + LC) because it is characterised by FinTechs using marketplaces for the provision of payment or deposit and lending services to a wide range of customers for a commission fee. Compared to cluster 3, it contains more FinTechs which also utilise marketplaces (to a lesser extent also transaction processing systems) and has a diverse mix of customers both in terms of their type and geographic segmentation. Their revenue model is also almost equally dominated by commission fees and interest income. Based on the archetypes in Eickhoff et al. (2017) it is a mixture of payment service archetype and lending community archetype.

We conducted also a cluster analysis of FinTech business model dimensions of Lee and Teo (2015). This led to the identification of two clusters of FinTechs with 100 FinTechs in cluster 1 and 97 FinTechs in cluster 2. The composition of the clusters by countries exhibits some interesting results (see Table 7). As can be seen from Table 7, 66 (93%) of FinTechs from Russia fall into the first cluster leading to a result where Russian FinTechs account for 66% of FinTechs within cluster 1. The proportion of FinTechs from other countries in cluster 1 is 36% or below.

When looking at the number of FinTechs by the main field of activity in the two clusters (see Panel A in Table 8), most investment

Table 6
Dominant characteristics of identified clusters.

Variable	Cluster 1 (LC)	Cluster 2 (LC + PS + O)	Cluster 3 (PS)	Cluster 4 (PS + LC)
Activity	Deposit and lending	Deposit and lending; banking infrastructure; payments	Payment	Payment; deposit and lending
Employees (most popular category)	10–25 employees	1–9 employees	1–9 employees	10–25 employees
Employees (average number of employees)	93.7	58.1	41.7	42.4
Local employees (average % of all employees)	12.3	74.2	99.2	43.5
Dominant technology	Marketplace	Marketplace; digital platforms	Transaction processing system	Marketplace; transaction processing system
Value proposition	Monetary; transparency; financial risk; usability	Intermediation; usability	Usability	Usability
Delivery channel	Physical connection; web application	APIs; web application	Web application; web application + mobile application	Web application; web application + mobile application
Customer type	B2C	Both; B2B	B2B	Both
Geographic segment	International	Local	Local	Both
Fixed costs to assets – average based on a scale 1 to 6 (highest)	2	5	4	4
Revenue model	Interest income	Commission income	Commission income	Commission income; interest income

Source: compiled by authors.
Notes: Average number of employees is calculated as a weighted average based on the midpoint of each size category (category more than 250 employees taken as 250).

Table 7
Number of FinTechs by home country in clusters based on Lee and Teo (2015) business model dimensions.

Country	Cluster 1	Cluster 2	Total
Estonia	6	25	31
Latvia	5	16	21
Lithuania	7	22	29
Poland	16	29	45
Russia	66	5	71
Total number of FinTechs	**100**	**97**	**197**

Source: compiled by authors.

Table 8
Characteristics of clusters based on Lee and Teo (2015) business model dimensions.

Panel A. Distribution of the number of FinTechs by field of activity	Cluster 1	Cluster 2	Total
Analytics	7	10	17
Banking infrastructure	23	18	41
Deposit and lending	34	24	58
Distributed ledger technology	1	9	10
Insurance	1	2	3
Investment management	10	4	14
Payment	24	30	54
Panel B. Mean evaluation by respondents (scale 1 to 6)	Cluster 1	Cluster 2	Difference
Profit margin	3.85	4.19	−0.34
Fixed costs to assets	3.73	3.38	0.34
Ability to scale	5.02	1.84	3.18
Innovative	4.70	1.89	2.81
Ease of compliance (regulatory requirements)	4.66	5.04	−0.38

Source: compiled by authors.

management FinTechs are in cluster 1 and most distributed ledger FinTechs in cluster 2. FinTechs focusing on other activities seem to be more evenly divided between the clusters. The differences in average evaluations across clusters are presented in Panel B in Table 8. The indicators for profit margin and fixed costs to assets are more favourable for FinTechs in cluster 2. However, the remaining three indicators are significantly better in cluster 1 compared to the ones in cluster 2. Considering the dominance of Russian FinTechs in cluster 1, the differences in the scalability and innovativeness dimensions can be directly linked to the optimistic responses of Russian FinTechs (see discussion in sub-Section 4.1.6). As the evaluations were made by the respondents, we would emphasise the superiority of the results obtained from the cluster analysis using Osterwalder and Pigneur (2010) business model attributes.

4.3. Connecting the dots

Based on the differences in the FinTech ecosystems, we expected to observe country-specific differences in FinTech business models in the selected countries. In line with expectations, we observe several significant differences at the end of 2019. First, the main activities of FinTechs vary significantly. FinTechs in Estonia are more active in distributed ledger technology, in Lithuania in payments and in Latvia in deposit and lending. Polish and Russian FinTech market remains more balanced across types of FinTech activities. These differences can be explained with the peculiarities of local country-specific conditions, which play an important role in the development of FinTechs. This result also exemplifies that the development of FinTechs remains dependent not only on international conditions but also on local conditions as also supported in Laidroo and Avarmaa (2020).

Second, the activities of FinTechs are strongly influenced by the maturity of the FinTech market. Latvian market is the most mature with the lowest levels of FinTechs under construction and the greatest proportion of FinTechs spending most of their time running daily business. The Russian market is the least mature (43% of respondents under construction) with FinTechs spending their time more frequently mainly on programming compared to running their business or marketing. This tendency supports the view that Moscow and St. Petersburg can be viewed as emerging FinTech hubs (CCAF, 2018).

Third, the current resource needs of FinTechs vary across countries. Estonia and Poland have the biggest concentration of very small FinTechs with over 40% of FinTechs having less than 10 employees. While in Latvia we observe 30% of FinTechs with more than 250 employees. These differences relate to the different activity profiles and maturity of FinTechs. Still, most FinTechs (irrespective of their location) refer to moderate or large expected growth in their employee count. This reflects the continuing growth potential of the sector.

Fourth, significant differences are observed in the types of customers FinTechs mainly serve. In Estonia and Poland, the greater focus seems to be on the provision of B2B services, in Latvia tilted towards B2C services. Even more striking differences are observed in the context of customers' geographic segmentation. Smaller countries (Estonia, Lithuania, Latvia) focus more strongly on international customers while bigger countries (Poland and Russia) with a big home market focus mainly on the local market. The level of internationality of sales seems also to be reflected in the location of employees, with Estonian and Latvian FinTechs exhibiting greater proportions of employees located outside of the company's home country. The latter result indicates that FinTechs with a home base in a smaller country may be able to develop superior business models, which are competitive globally. Although FinTechs located in big countries have a big home market advantage, it may hinder their international growth potential.

Fifth, when evaluating the success factors of FinTechs by dimensions suggested by Lee and Teo (2015), the outlier seems to be Russia where managers indicate that their FinTechs are significantly more innovative, able to scale, and are in a better position when complying to regulatory requirements. As the gap between Russia and other countries is so large, at least part of this result seems to arise from a possibly too optimistic outlook of Russian FinTech managers. Still, we acknowledge that the big home market provides very good possibilities to scale, and weaker institutions (as shown in Table 3) may expose FinTechs to a lower level of regulatory pressure than in other countries. High evaluation of innovativeness could relate to a bit lower level of sophistication in average financial services provision, which is reflected for example in the use of mobile or Internet for accessing an account.

We also see that the main activity of the FinTech has a strong association with its other business model attributes. More mature FinTech activities are associated with greater resource use. For example, FinTechs in the field of deposit and lending and investment management have significantly more employees and lower employment growth than those in distributed ledger technology. The dominant technology partly defines the FinTech activity. Therefore, it is not surprising that deposit and lending FinTechs rely more on marketplace technologies, payments on transaction processing systems, and distributed ledger technology on blockchain. Although usability appears a key value proposition for all FinTech activities, more distinct value propositions appear in deposit and lending and banking infrastructure. Consumer-orientation remains superior to business-orientation in FinTechs providing payments and banking infrastructure services and the delivery channels vary significantly across types of FinTech activity. Revenue sources correspond to the type of FinTech with payment FinTechs relying on commission income, deposit and lending FinTechs both on commission and interest income, and FinTechs in analytics on income from data.

Cluster analysis based on Osterwalder and Pigneur (2010) framework revealed that the FinTechs in the five countries can be divided into four clusters: "lending community", "mixed services", "payment service", and "payment community". These clusters exhibited characteristics very similar to the three FinTech archetypes reported by Eickhoff et al. (2017). This indicates that their FinTech taxonomy has clear applicability in practice and some business model characteristics of FinTechs in the selected countries remain rather "standard". Still, we did observe that the business models of Russian and Estonian FinTechs were significantly more versatile (being the least versatile in Poland). This confirms the cross-country differences observed while looking at business model attributes of specific FinTechs. It also indicates that although some aspects of FinTech business models share similar traits globally, local conditions seem to play an important role in shaping the business models of individual FinTechs.

5. Concluding remarks and future research directions

The objective of this paper was to determine the differences in business model attributes of FinTechs in Estonia, Latvia, Lithuania, Poland, and Russia. The FinTech ecosystem scores referred to some distinct differences in local conditions. As expected, these seemed to explain some of the observed differences in business models of FinTechs across countries. As we did not take a closer look at the specifics of local conditions, further research is needed into more qualitative aspects of the functioning of local FinTech ecosystems and how that influences the development of FinTech business models over time. Without such deeper understanding policy-makers and entrepreneurs are acting blindfolded. The same reasons also highlight the need for more comparative research in the business models of FinTechs in other countries, as previously highlighted by Iman (2020) and Kavuri and Milne (2019).

Four main FinTech business model clusters identified in this paper exhibit some basic characteristics that are more or less similar to payment service, lending community, and financial markets intermediary archetypes proposed by Eickhoff et al. (2017). Although some common traits with archetypes exist, the attributes of Fintech business models differ in the five countries analyzed. This refers to the relevance of local conditions in shaping the business models of individual FinTechs. Our results support also the notion that the business model of FinTech is not equivalent to its main activity, as considered in some earlier works (e.g., Lee and Shin, 2018; Liu et al., 2020). As significant changes in FinTech business models are expected to continue, further research is needed into the gradually evolving attributes of FinTech business models.

Our results do remain vulnerable to several limitations. First, the results cannot be directly extended to other countries and within the selected countries outside of the selected timeframe. This relates to business models of specific FinTechs being influenced by local conditions and ecosystems, as well as to the possible changes in conditions and business model attributes over time. Second, three of the business model dimensions analysed in the paper were backfilled by the authors unlike other business model attributes, which were gathered through survey responses. Third, although the representativeness of the sample across the whole dataset is good, it remains below desired levels on a country-level for two countries. Therefore, country-specific results need to be interpreted with caution. Fourth, since there is no official list of FinTechs, some FinTechs may have remained outside of the scope of the paper. Eventually, the surveys were run before the COVID pandemic, and the sentiment of the respondents may have changed during 2020.

Despite these limitations, the paper provides unique comparative evidence on the development of FinTech business models in emerging European FinTech hubs. It also demonstrates that the "traditional" Osterwalder and Pigneur (2010) business model canvas can be easily utilised for the investigation of FinTech business models. Especially, if it is simultaneously considered with FinTech specific aspects determined by Eickhoff et al. (2017). Policy-makers and entrepreneurs can benefit from the use of this approach to understanding the local FinTech landscape.

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CRediT authorship contribution statement

Laivi Laidroo: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Project administration. **Ekaterina Koroleva:** Investigation, Writing - original draft, Writing - review & editing. **Agata Kliber:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Ramona Rupeika-Apoga:** Conceptualization, Investigation, Writing - original draft, Writing - review & editing. **Zana Grigaliuniene:** Investigation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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