BACKGROUND PAPER

Digital Framework Conditions and the Productivity Potential of a Country's Entrepreneurial Dynamic: A Study of Selected ADB Member Economies

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DISCLAIMER

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I. INTRODUCTION

Entrepreneurship is generally considered an important driver of economic growth (Acs and Szerb 2007; Audretsch, 2018; Wong, Ho, and Autio 2005). This is mainly because of the important role that entrepreneurs can play in allocating resources towards productive uses (Acs, Autio, and Szerb 2014). Given the right conditions, individuals can be motivated to recognise entrepreneurial opportunities – i.e., spot situations where it is possible to create and sell goods and services at a price that is higher than the cost of their production (Eckhardt and Shane 2003; Klein 2008). If individuals in the economy are motivated to recognise and assess opportunities, and if the option of pursuing those opportunities through an entrepreneurial firm offers a higher prospective return to invested effort than do alternative allocations of the individual's human and social capital, then those individuals are more likely to engage in *productive entrepreneurship,* that is, entrepreneurial activity that allocates resources in the economy towards productive uses that ultimately help lift Total Factor Productivity (TFP) (Acs et al. 2014; Autio and Acs 2010; Baumol 1990).

However, not all entrepreneurial activity allocates resources towards productive uses. As Baumol (1990) already observed, entrepreneurship can be productive, unproductive, and even destructive. Productive entrepreneurship allocates resources towards uses that yield higher productivity than in alternative uses. Unproductive entrepreneurship allocates resources towards unproductive uses that do not significantly contribute to the TFP in the economy. Destructive entrepreneurship destroys TFP in the economy, e.g., by destroying productive resources or by creating such significant negative externality that the net outcome for economic productivity is negative. While innovative entrepreneurship is generally considered as productivity-enhancing, much of micro-entrepreneurial activity tends to be unproductive (e.g., street vendors whose human capital might be employed more productively in alternative occupations). Examples of destructive entrepreneurship include, e.g., criminal activity (e.g., drug dealers) and inefficient, extractive and unsustainable entrepreneurship that depletes common-pool resources.

Given that entrepreneurial activity can be productive, unproductive, and even destructive, increased levels of entrepreneurship do not automatically lead to economic growth. Indeed, the Global Entrepreneurship Monitor (GEM) survey – which annually surveys self-employment activity in a group of some 60-70 countries – consistently reports *negative* correlations between a given country's gross domestic product (GDP) per capita and its level of overall self-employment activity (Acs et al. 2014). This in fact, only a very small portion of all new self-employed who can be expected to generate a non-trivial contribution towards TFP. These considerations raise an important question: When and under which conditions do

entrepreneurs contribute to economic growth? More specifically, what are the factors that regulate the quality of the entrepreneurial dynamic in a given economy, in terms of the ability of this dynamic to drive TFP? Under which conditions are entrepreneurs likely to drive the allocation of resources towards activities that enhance TFP, and under which conditions are entrepreneurs likely to drive the allocation of resources away for high-productivity activities?

These questions have important implications for entrepreneurship policy (Audretsch 2018). in general, enhancing entrepreneurship makes little sense if the resulting economic activity does not drive, or worse, even deducts from economic growth and development. Therefore, it is important to study the conditions that regulate the potential contributions of a country's entrepreneurial dynamic to economic development and growth. In this study we combine wide-coverage cross-country data on individual-level entrepreneurial activity with country-level descriptors of a country's digital framework conditions (DFCs) to explore the effect of these on the productivity potential of the country's entrepreneurial dynamic.

In this study, we define entrepreneurship as an individual (or team) -level occupational choice that is made by rational individuals who seek to maximise the returns of their allocation of their human, social, and financial capital through the pursuit of entrepreneurial opportunities instead of (or in parallel with) alternative occupations (Autio and Acs 2010). We consider the pursuit of entrepreneurship to normally require sustained allocation of effort and resources, in the form of the individual's and entrepreneurial team's human, social, and financial capital. As these resources are finite, the allocation of them to one activity means that they normally cannot be simultaneously allocated to another use. The decision to pursue an entrepreneurial opportunity means that an individual normally cannot simultaneously pursue an alternative occupation. The rationality assumption implies that the individual will allocate their human, social, and financial capital towards occupations that promise the greatest return to those allocations. Finally, we assume that the country's prevailing framework conditions regulate the trade-offs between alternative occupational pursuits by influencing the balance of expected returns to alternative occupations.

This report progresses as follows. We first review received findings regarding the effect of national-level framework conditions on entrepreneurship. We then elaborate our empirical model, which focuses specifically on what we call national-level DFCs. We then explain our methods and data. After this we discuss our findings. We conclude with discussion and policy implications.

II. PRODUCTIVE AND UNPRODUCTIVE ENTREPRENEURSHIP

In this report, we treat entrepreneurial activity as an individual-level initiative: entrepreneurial opportunities are pursued by individuals and teams of individuals who allocate their human and financial resources towards the pursuit of perceived profit-making opportunities, using a new independent firm as the vehicle. We also treat entrepreneurial activity as fundamentally economic: the pursuit of opportunities to sell goods and services at a price higher than the cost of their production (Armour and Cumming 2008; Eckhardt and Shane 2003; Seung-Hyun, Peng, and Barney 2007; Thomas 2000). As this definition holds, entrepreneurial activity is likely to emerge when there is an opportunity for economic profit. Given that entrepreneurial opportunity pursuit entails the allocation of the entrepreneurial team's human and financial resources in varying degrees, the size of this opportunity–and therefore, the likelihood of opportunity pursuit actually occurring–depends on the opportunity cost of the required resource allocation, on the one hand, and on the market price of the products and services offered, on the other. Given that the opportunity costs of resource allocation will vary by individual and resource, a given situation may represent a first-person opportunity to someone (i.e., an "opportunity for me") and a third-person opportunity for someone else (i.e., "an opportunity for someone but not necessarily for myself") (McMullen and Shepherd 2006). The more valuable human and other resources a given individual possesses (e.g., in the form of valuable education), the larger the profit potential offered by a given third-person opportunity needs to be for it to be judged to be a first-person opportunity for that individual.

At the country level, we may expect entrepreneurial activity to be quite heterogeneous, reflecting the ability of the economy to generate third-person opportunities for entrepreneurial activity and the heterogeneity of resources individuals can draw upon for entrepreneurial opportunity pursuit (Autio and Acs 2010). Not all entrepreneurial activity enhances TFP. Because a given set of resources may typically be allocated towards one use only (e.g., to the pursuit of a given first-person opportunity), the allocation of resources entails opportunity costs not only to the individual, but also, from the perspective of the wider economy. If entrepreneurial opportunity pursuit entails the allocation of valuable resources to low-yield activity, the country's Total Factor Productivity may suffer if those resources could have been deployed more productively elsewhere. For example, if a highly educated medical doctor decides to become a self-employed taxi driver, that individual's human capital will not be available for deployment in the provision of specialist medical services, where that human capital could find a more productive use. In contrast, if a given individual has received only basic education, an occupation as a self-employed taxi driver may well

represent the most productive use of that person's human capital, and the allocation therefore should result in a positive contribution towards the country's TFP.

At the country level, therefore, the entrepreneurial resource allocation dynamic has the potential to contribute to the economy's TFP either positively or negatively, depending on a myriad of individual-level resource allocation choices (Acs et al. 2014). We assume that these choices are ultimately made by the individual, who seeks to maximize the return to his or her human capital and other resources. This choice involves the weighing of trade-offs regarding alternative potential uses of those resources. To the extent that the pursuit of a given entrepreneurial opportunity increases the anticipated return to the associated resource allocation, we may expect entrepreneurial activity to materialize.

In this report, we are interested in factors that regulate the trade-offs that are associated with entrepreneurial resource allocation. In addition to the intrinsic quality of entrepreneurs' resources, we expect that this resource allocation may be influenced by country-level Entrepreneurial Framework Conditions, or EFCs (Levie and Autio 2008). EFCs are country-level factors that condition the allocation and appropriation of returns resulting from economic activity such as entrepreneurial opportunity pursuit (de Soto 2000). Examples of EFCs include regulations that govern the creation of new firms (Djankov, La Porta, Lopez-de-Silanes, and Shleifer 2002a; Klapper, Laeven, and Rajan,2006), employment regulations (Botero, Djankov, La Porta, Lopez-de-Silanes, and Shleifer 2004), and the quality of the country's political and economic institutions, which may either enhance or undermine the appropriation of economic returns to resource investment in entrepreneurial opportunity pursuit (Autio and Fu 2015; Autio, Fu, and Levie 2019b; Djankov, Lieberman, Mukherjee, and Nenova 2002b), such as the country's rule of law regime (Djankov, La Porta, Lopez-de-Silanes, and Shleifer 2003). In previous research, the country's institutional conditions have been shown that more onerous regulations governing new firm creation will dampen the entry of new firms by pushing up the cost of resource allocation to entrepreneurial opportunity pursuit (Djankov et al. 2002a). Onerous entry regulations may also push entrepreneurs to avoid registering their business and choose to operate in the informal sector instead (Autio and Fu 2012, 2015; Djankov et al. 2002b). As firms operating in the informal sector may gain an advantage over registered new businesses, e.g., by avoiding taxes and licensing costs, a high prevalence of informal-sector may inhibit entry and growth aspirations by high-quality formal-sector entrepreneurs (Autio et al. 2019b). Onerous employment regulations may inhibit entrepreneurs from seeking to grow their businesses, thereby hampering their productivity potential (Botero et al. 2004). Poor-quality economic and political institutions and associated corruption similarly may dent the confidence of prospective and new entrepreneurs to invest, thereby

hampering the productivity potential of the country's entrepreneurial resource allocation dynamic (Autio and Fu 2015; Djankov et al. 2003).

In this paper, we are interested in a specific category of EFCs: the country's DFCs for entrepreneurship. During recent decades, countries' digital infrastructures (e.g., the telecommunications infrastructure, the Internet infrastructure, digital resources available and accessible therein) have grown to become increasingly important regulators of economic activity (Tilson, Lyytinen, and Sørensen 2010; Yoo, Boland Jr, Lyytinen, and Majchrzak 2012). As economic and societal activities become increasingly digitalized[1], this development enables new ways of organising economic activities for the discovery, creation, delivery, and capture of economic value. Because of the potency of the "Moore's Law", which effectively states that the unit cost of digital processing power doubles every 18 months, translating into a doubling of computing power accessible with a given amount of money during the same time, business firms are being supplied with a virtual explosion of opportunities to harness digital technologies and infrastructures in novel ways for value creation and capture. This explosion of digital affordances has driven a virtual explosion of business model innovation opportunities, or opportunities to re-think how businesses organise for the creation, delivery, and capture of economic value. The bulk of these opportunities are being exploited by new, entrepreneurial businesses (Autio, Nambisan, Thomas, and Wright 2018a; Thomas, Sharapov, and Autio 2018). Other visible manifestations of the transformative impact of digitalization on the economy include the emergence of the "platform economy" and the concomitant emergence of "platform ecosystems" and "innovation ecosystems" as an important form of organising collective action for value co-production (Van Alstyne, Parker, and Choudary 2016).

Given the importance of digitalisation as an enabler of innovative entrepreneurial activity, it is surprising that there has been little research to explore the effect of country-level DFCs on the quality of the country's entrepreneurial resource allocation dynamic (Autio, Szerb, Komlósi, and Tiszberger 2018b). In this report, we undertake such exploration. Specifically, we expect advances in digital technologies and infrastructures to improve the quality of the country's entrepreneurial dynamic by making third-person entrepreneurial opportunities more easily accessible by those individuals and teams whose human and other resources are valuable and therefore carry high opportunity costs to resource allocation. Digitalisation has the effect

[1] Digitalization is the implementation of digital technologies in economic and societal processes such that these become infra-structural.

of reducing the opportunity cost of resource allocation towards entrepreneurial opportunity pursuit for five reasons:

1. Digital commons lower the cost of opportunity pursuit by allowing entrepreneurs to substitute expensive and privately-held freely accessible digital commons resources (Dulong De Rosnay and Stalder 2020)
2. Because digital affordances enable efficient creation and coordination of novel value-creating combinations, they open attractive entrepreneurial opportunities that established incumbent firms may have difficulty addressing because of their investment in legacy business models (Autio et al. 2018a)
3. Digital infrastructures reduce the cost of internationalisation and scaling-up of the new business firm, thereby extending the upside potential of entrepreneurial opportunity pursuit (Mograbyan and Autio 2021)
4. By enabling extensive outsourcing of activities, digital technologies and infrastructures lower the cost of entrepreneurial entry (Bardhan, Whitaker, and Mithas 2006)
5. Digital technologies enable low-cost experimentation with alternative value offerings, thereby reducing the downside potential of entrepreneurial opportunity pursuit (Andries, Debackere, and Van Looy 2013; Kerr, Nanda, and Rhodes-Kropf 2014)

Digital commons are freely accessible digital technologies and infrastructures (Dulong De Rosnay and Stalder 2020; Legenvre, Autio, and Hameri 2021). They include open-source technologies such as open-source software and hardware, open data, and freely accessible application programming interfaces. Digital commons can be harnessed for the creation of value-adding innovative outputs at low cost, thereby reducing the resource investment required to launch a new entrepreneurial business. By harnessing digital commons, the new firm can create valuable outputs at lower cost (e.g., mobile applications that harness freely accessible software libraries; or harnessing freely accessible web design platforms to design attractive web pages for the new business). Lowered resource costs of starting a new business lower the barrier to invest and increase the chances that individuals possessing high-quality resources will allocate these to entrepreneurial opportunity pursuit over alternative occupational pursuits. High-quality DFCs should, therefore, enhance the quality of a country's entrepreneurial dynamic by reducing the opportunity cost of resource allocation to entrepreneurship. We expect this effect to show up as an increased prevalence of innovative entrepreneurial entries.

Digital affordances open opportunities to perform desired functions more effectively than before and enable the performance of completely novel functions that were previously not possible (Autio et al. 2018a). The rapid increase in the power and functionalities of digital technologies enables the automation of complex and increasingly knowledge-intensive tasks, as it becomes increasingly possible to code them in algorithmic form. In addition to the automation and execution of knowledge-intensive tasks and functionalities, digital technologies provide particularly potent affordances for coordination and communication, thereby enabling even radical re-think of how to organise and coordinate organisational activities for value creation, delivery, and capture – i.e., how they organise their business models. Because established incumbents tend to have optimised their value-creating activities around conventional business models, they are often inhibited in their ability to radically rethink their organizational architectures to take advantage of the new digital affordances. Because new firms are not inhibited by their legacy investments, this situation opens lucrative opportunities for them to challenge incumbents with radical business models, as testified by cases such as Grab. High-quality DFCs should therefore encourage high-quality entrepreneurial entry by opening lucrative business model disruption opportunities for new firms to exploit. We expect this effect to show up as an increased prevalence of entrepreneurial entries that exploit process innovations.

Digital technologies and infrastructures are also inherently borderless and scalable. Businesses that harness digital technologies in their business models tend to be able to easily scale up their offerings without needing to invest heavily in physical assets. As the Internet and digital resources accessible therein are relatively blind to national borders, it is easy for even new and small start-up firms to make their offerings available to customers in other countries. Internet reintermediation platforms such as Alibaba and eBay allow new firms to make their offerings discoverable to wide audiences, thereby widely expanding their demand potential. The combination of the two features—cross-border visibility and easy scalability—should tilt the trade-off between entrepreneurial opportunity pursuit and other occupational choices in favor of the entrepreneurial option, because they help boost the potential upside rewards of the entrepreneurial option. High-quality DFCs should therefore enhance the productivity potential of entrepreneurial entries because of their effect on the international scalability of these. We expect this effect to show as an increased prevalence of high-growth and export-oriented entrepreneurial entries.

The coordination potency of digital technologies has greatly expanded the ability of firms of any size to outsource business activities and processes from specialised suppliers, thereby enabling businesses to focus on exploiting their distinctive capabilities (Lahiri and Kedia 2011; Mani, Barua, and Whinston 2010). Since the turn of the millennium, this trend has expanded beyond the traditional outsourcing of

manufacturing activities towards increasingly knowledge-intensive activities, and the trend has also been increasingly impacting even new and small firms (Di Gregorio, Musteen, and Thomas 2008). Business process outsourcing is beneficial for new firms, since it allows the firms to specialise in exploiting their distinctive capabilities while side-stepping the cost of developing the full set of organisational capabilities conventionally required of a going concern (e.g., marketing, sales production, and research and development [R&D] capabilities) (Symeonidou, Leiponen, Autio, and Bruneel 2022). This both reduces the cost of entrepreneurial entry and the risk of it by allowing the new venture to achieve competitive distinctiveness and reach legitimation proofpoints sooner, thereby reducing downside risks of entrepreneurial entry. High-quality DFCs should therefore make entrepreneurial entry more attractive particularly for innovative start-ups that might otherwise be inhibited from entry because of the resource investment required to develop a full repertoire of organizational capabilities. We expect this effect to show as an increased innovativeness of entrepreneurial entries.

Finally, digital technologies have made it possible for new firms to modify their value offerings easily and costlessly to experiment with different value propositions and receive virtually instant feedback (Andries et al. 2013; Björklund, Mikkonen, Mattila, and Van Der Marel 2020). This effect is so potent that it has helped introduce a novel approach to new firm start-up, commonly referred to as the "Lean Entrepreneurship" heuristic (Blank, 2013; Ries 2011). The ability to quickly experiment with, test, and validate alternative value offerings at low cost significantly reduces the risks associated with the launch of new start-up companies (Bocken and Snihur 2020). This is particularly important for innovative start-ups, since value offerings exhibiting a high degree of novelty are inherently more risky and uncertain than are more conventional value offerings that are not different from established value offerings that have already been proven in the marketplace. Therefore, we expect high-quality DFCs to lower the threshold of innovative entrepreneurial entry.

Summarising our reasoning, we posit the following general hypothesis for empirical testing:

Hypothesis 1 *The quality of a country's DFCs for entrepreneurship should be positively associated with the quality of that country's entrepreneurial dynamic, as expressed in the population prevalence of innovative, growth-oriented, and export-oriented entrepreneurial activity.*

III. Entrepreneurship in ADB Regional Member Economies

We are interested in the quality of the entrepreneurial dynamic in regional member economies of the Asian Development Bank (ADB). As outlined in the preceding section, we assume that this quality is influenced by a country's DFCs for entrepreneurship. Therefore, we conduct two sets of analyses. The first of these provides descriptive data on individual-level entrepreneurial activities in a sample of ADB member economies. This descriptive analysis is conducted to illustrate the heterogeneity of individual-level entrepreneurial activities in ADB member economies. For this analysis we use data from the GEM to illustrate heterogeneity in firm-level productivity potential in all ADB regional member economies for which GEM data is available for years 2010 - 2019[2]. For this descriptive analysis, we use a sample of 17 ADB member economies, as detailed below.

In the second part of our analysis, we explore associations between country-level Digital Framework Conditions (DFCs) and individual-level entrepreneurial activity. For this analysis, we use all ADB member economies for which we have available GEM data for years 2010 – 2019, and for which we also have data on country-level Digital Framework Conditions. For this analysis, we therefore use a sample of 17 ADB member economies, as detailed in the section following the descriptive analysis.

Below, we provide a descriptive analysis to illustrate heterogeneity in firm-level productivity potential in the 17 ADB member economies for which GEM data is available for years 2010 – 2019. We use publicly available data from GEM dataset for data on entrepreneurial attitudes, activities, and aspirations by individuals (Reynolds et al. 2005). GEM is an annual survey of entrepreneurial activity that applies harmonised data collection methods to compile population-representative samples of individuals across participating countries. GEM data is collected annually in each country in interviews of at least 2 000 individuals per country. More than 70% of the data is collected by telephone interviews, and the rest is collected in face-to-face interviews using multistage randomized cluster sampling. The resulting raw data is weighted using relevant demographic variables such as age, gender, education, ethnicity, and other variables such that the resulting weighted dataset is representative of the country's working-age population (individuals from 16 to 64 years of age).

For the descriptive analysis, our GEM dataset is drawn from interviews of a total of 214,496 individuals from ADB's 17 regional member economies for years 2010–2019. This data is pooled by country.

[2] Our dataset covers all regional ADB member economies for which GEM data is available for all or any of the years 2010-2019: Bangladesh; the People's Republic of China; Georgia; Hong Kong, China; India; Indonesia; Kazakhstan; Malaysia; Pakistan; the Philippines; Singapore; the Republic of Korea; Taipei,China; Thailand; Armenia; Vanuatu; and Viet Nam

The GEM survey tracks individual-level entrepreneurial activity in countries. The survey uses several screening questions to determine whether an individual is currently running or trying to start, a new, entrepreneurial business. The interviewed individual needs to respond affirmatively to the question of whether he or she is currently running or trying to start a new business, including any kind of self-employment activity. The individual will also need to indicate that they will personally own all or part of the business, and that they would actively participate in the management of the new business activity. The individual will also need to confirm that they are not trying to start the new business on behalf of their employer, as this would be a form of corporate entrepreneurship, which is not the focus of our current analysis.

The GEM survey uses further criteria to distinguish between nascent, new, and established businesses. If the business has not yet paid wages or salaries to anyone (including the owner-manager(s)), or if it has paid wages or salaries to anyone for up to three months only, the new business is qualified as a 'nascent' entrepreneurial business. If the business has paid wages or salaries to anyone for at least three months but no longer than 42 months, the new business is qualified as a "baby business". If the business has paid wages or salaries for longer than 42 months, it is qualified as "established business". In the descriptive analysis that follows, we focus on baby businesses entrepreneurial businesses only.

In total, our dataset includes 14,892 (population weighted) baby businesses, which were owned and managed by individuals and teams of individuals, were not being started on behalf of the individual's employer, and which had paid salaries or wages for at least three months but not for longer than 42 months. In addition, our sample includes 22,617 (population weighted) established entrepreneurial businesses that had paid salaries or wages to someone for longer than 42 months (Table 1).

Table 1: Distribution of Entrepreneurs in the Sample of 17 ADB Member Economies

ADB Member Economy	Total Businesses	% of Total	Baby Businesses	% of Total	Established Businesses	% of Total
China, People's Republic of	37,708	17.6	2,884	19.4	3,300	14.6
India	27,436	12.8	1,130	7.6	1,638	7.2
Indonesia	24,710	11.5	2,773	18.6	3,554	15.7
Thailand	20,772	9.7	2,159	14.5	4,953	21.9
Korea, Republic of	19,481	9.1	970	6.5	1,813	8.0
Taipei,China	18,002	8.4	959	6.4	2,113	9.3
Malaysia	16,107	7.5	609	4.1	1,052	4.7
Singapore	8,405	3.9	307	2.1	256	1.1
Kazakhstan	8,118	3.8	328	2.2	311	1.4
Philippines	8,009	3.7	623	4.2	475	2.1
Viet Nam	8,007	3.7	1,146	7.7	1,686	7.5
Pakistan	6,500	3.0	195	1.3	343	1.5
Hong Kong, China	4,032	1.9	86	0.6	133	0.6
Georgia	2,027	0.9	131	0.9	292	1.3
Armenia	2,000	0.9	144	1.0	156	0.7
Bangladesh	2,000	0.9	133	0.9	231	1.0
Vanuatu	1,182	0.6	315	2.1	311	1.4
Total	214,496	100.0	14,892	100.0	22,617	100.0

Source: Authors

Table 2 shows the employment size of both baby businesses and established businesses at the time of the interview. Of the baby businesses, 51% qualified as micro businesses that employed at most two employees including the owner-manager(s). Of the established businesses, the corresponding share was almost exactly the same: 51.2% of the sample total. In contrast, entrepreneurial businesses with 250 or more employees represented only 0.4% of both baby businesses and established businesses in the sample.

The number of firms belonging to the smallest employment size category was roughly two orders of magnitude (i.e., more than 100-fold) larger than that of the firms belonging to the largest employment size category in both age groups. However, the contributions of these two categories to total employment generated by baby businesses and established businesses were dramatically different. Whereas micro businesses had generated 8.2 % and 7.7% of the total employment by baby businesses and established businesses, respectively, baby businesses and established businesses with over 250 employees had generated more than 45% of the total employment in both baby businesses and

established samples.[3] This pattern is well known as such but quite dramatic, nevertheless. There were more than 100 times more micro businesses in the sample than there were large businesses (250 employees or more). Yet, the large businesses generated close to six times as much employment in total as did the micro businesses. In other words, the firm-level employment potential of a new entrepreneurial business that grows to the largest employment size category is roughly 600 times that of a typical micro business.

It is interesting that the share of both the smallest and largest employment categories is practically exactly the same among baby businesses and established businesses, respectively. Also, the proportions of the firms falling into the middle employment categories (3-9 employees, 10-49 employees, and 50-249 employees) were virtually the same among baby businesses and established businesses. The average number of employees per business were almost the same: 8.9 employees per baby business and 9.2 employees per established business. Thus, the firm-level average employment size does not seem to grow over time at the population level, and the distribution of employment sizes within the population appears much more important[4].

Table 2: Current Employment in Baby Businesses and Established Businesses in the Sample of 17 ADB Economies

	Baby businesses (up to 42 months old)				**Established businesses** (older than 42 months)			
Firm Size	Firms	%	Total Employees	%	Firms	%	Total Employees	%
0–2	7,602	51.0	10,888	8.2	11,570	51.2	15,928	7.7
3–9	5,900	39.6	25,695	19.5	8,777	38.8	39,252	18.9
10–49	1,169	7.8	20,240	15.3	1,907	8.4	33,381	16.1
50–249	166	1.1	14,401	10.9	270	1.2	25,119	12.1
250+	55	0.4	60,785	46.0	92	0.4	94,225	45.3
Total	14,892	100.0	132,009	100.0	22,616	100.0	207,905	100.0

Source: Authors

Table 3 shows a similar pattern when we look at the expected employment generation in five years' time, i.e., the self-reported number of employees that the firms expected to have within five years' time. This data illustrates the growth expectations of entrepreneurial businesses. As can be seen, the

[3] Note: data was winsorized with a maximum of 2,000 employees per business.
[4] Note that our data only covers firms that had not exited.

same pattern holds as above. These totals are mirrored by the expected employment impact, with micro businesses expecting to generate 3.3% and 5.4% of the total employment by baby and established businesses, respectively, and businesses with 250 or more expected employees responsible for 57.6% and 43.1% of total employment by baby and established businesses, respectively. For expected employment generation, the distribution of baby businesses is more skewed towards the larger employment size categories than for established businesses, perhaps reflecting the greater optimism by these or, alternatively, the greater realism by established businesses.

Table 3: Expected Employment Growth by Baby Businesses and Established Businesses in the Sample of 17 ADB Economies

	Baby businesses (up to 42 months old)				**Established businesses** (older than 42 months)			
Firm Size	Firms	%	Total employees	%	Firms	%	Total employees	%
0-2	6,555	44.0	8,667	3.3	10,158	44.9	13,914	5.4
3-9	5,733	38.5	26,242	9.9	9,184	40.6	42,306	16.5
10-49	1,993	13.4	34,292	12.9	2,707	12.0	46,744	18.3
50-249	477	3.2	43,584	16.4	455	2.0	42,749	16.7
250+	134	0.9	153,258	57.6	112	0.5	110,272	43.1
Total	**14,892**	100.0	**266,043**	100.0	**22,616**	100.0%	**255,985**	100.0

Source: Authors

Table 4 shows the export activity of baby businesses and established businesses in the 17 ADB member economies. In the sample, exporting status is measured by the proportion of the firm's customers who live outside of the country. It can be seen from the table that more than 26% of the baby businesses engaged in some exporting activity by serving customers in other countries, while some 20% of the established business did the same. The majority of the businesses had no export activity, with three quarters of the baby businesses and four fifths of the established businesses reporting no customers living in other countries. In addition, most of the exporting firms tended to have relatively small share of their customers in foreign countries, with 15.5% of the baby businesses and 12.6% of the established business having less than 10% non-domestic customers.

Table 4: Firm's Customers Live outside of the Country in a Sample of Entrepreneurial Businesses in 17 ADB Member Economies

	Baby Businesses (up to 42 months old)		**Established Businesses** (older than 42 months)	
Percentage of customers living outside the country	No. of Firms	% of Firms	No. of Firms	% of Firms
91–100	192	1.4	225	1.2
76–90	156	1.1	156	0.8
51–75	294	2.1	282	1.5
26–50	348	2.5	343	1.8
11–25	537	3.9	521	2.8
1–10	2,123	15.5	2,384	12.6
None	10,074	73.4	15,026	79.3
Total	13,724	100.0	18,937	100.0

Source: Authors

Similar skewness is also visible in the adoption of new technologies by the sample businesses. The respondents were asked to indicate whether the technologies required by the products, services, and processes of their businesses had been available for less than 1 year, between 1 year and 5 years, or for longer than 5 years. As can be expected, established businesses tended to use more established technologies, with some 74% of established businesses reporting to use technologies that had been available for longer than five years. Of the baby businesses, less than half used technologies that had been available for longer than 5 years, and over half of the baby businesses using more novel technologies.

Table 5: New Technology Adoption by a Sample of Baby Businesses and Established Businesses in 17 ADB Member Economies

	Baby Businesses (up to 42 months old)		**Established Businesses** (older than 42 months)	
	No. of Firms	% of Firms	No. of Firms	% of Firms
Less than a year	3,143	23.7	2,066	11.2
Between 1 and 5 years	4,049	30.6	2,795	15.1
More than 5 years	6,054	45.7	13,639	73.7
Total	**13,246**	**100.0**	**18,500**	**100.0**

Source: Authors.

Note that this data covers the GEM survey results from 2010 to 2018 as the question was framed differently in 2019 survey. It enquired about whether the technologies and procedures used by the business were new locally, nationally, or globally in GEM 2019.

A similar pattern is also exhibited for entrepreneurial businesses that offered new products or services that are unfamiliar to all or some of their customers. Of the baby businesses, 18.5% indicated that their product or service was new and unfamiliar to all of their customers. For established businesses, this percentage was 16.5%. Of the baby businesses, 34.5% indicated that their product or service was new and unfamiliar for some of their customers. For established businesses the corresponding figure was 25.5%. For roughly half of the baby businesses and 58% of the established businesses, none of their customers found their product or service new or unfamiliar.

Table 6: Unfamiliarity of the Firm's Product or Service for Customers in a Sample of Entrepreneurial Businesses in 17 ADB Member Economies

	Baby Businesses (up to 42 months old)		Established Businesses (older than 42 months)	
	No. of Firms	% of Firms	No. of Firms	% of Firms
All	2,470	18.5	3,053	16.5
Some	4,595	34.5	4,708	25.5
None will consider this new and unfamiliar	6,269	47.0	10,727	58.0
Total	**13,334**	100.0	**18,488**	100.0

Source: Authors

Note that this data covers the GEM survey results from 2010 to 2018, as the question was framed differently in the 2019 survey. The GEM 2019 survey enquired whether any of the firm's products or services were new to people who live locally, nationally, or globally.

In summary, our descriptive analysis confirms that entrepreneurial activity in ADB member economies is highly heterogeneous. Based on employment growth, roughly half of all new, entrepreneurial businesses in ADB economies will remain in the micro business category and employ at most 2 people. Combined, these micro businesses generated only some 10% of the total employment created by new, entrepreneurial businesses. On the other extreme, only less than 0.5% of new, entrepreneurial businesses reach the size of 250 or more employees, yet these super-growth businesses create nearly half of all new employment by entrepreneurial businesses. This is very significant bias that signals that out of 200 new businesses, only one will be a true job creator. Similar biases can also be observed in terms of export activity, where only less than 5% of entrepreneurial businesses had the majority of their

customers in other countries, and some 75% reported no foreign customers at all. The bias was less pronounced for product innovation, where nearly half of the entrepreneurial businesses self-reported that their product or service was new to at least some of their customers.

In all, these findings signal non-trivial heterogeneity in new firm populations in terms of their ability to scale, internationalise, and innovate, thereby contributing to the TFP of the economy. The important message for policy here is that “one size fits all” policies may not be very effective in nurturing the productivity potential of entrepreneurial and new firms in the economy. Targeted policies would likely be more effective but raise the difficult question of how to identify and nurture potential winners – a task that governments are not so well equipped to undertake (Autio and Rannikko 2016). However, instead of trying to pick winners, there are also other ways with which governments could seek to enhance the productivity potential of the entrepreneurial dynamic. Potentially a better approach for governments could be to try and influence the trade-offs associated with an entrepreneurial career choice such that the entrepreneurial option becomes more attractive for individuals who possess valuable human and social capital and financial and other resources. This can be done by influencing country-level framework conditions for entrepreneurship (Acs et al. 2014). In the digital age, one important set of such framework conditions is represented by what we call the country’s DFCs for entrepreneurship. As theorised in the theory section of this report, high-quality DFCs should facilitate a high-quality entrepreneurial dynamic by making it more attractive for individuals to allocate high-quality resources towards the pursuit of entrepreneurial opportunities. We next conduct an analysis of the impact of DFCs on the quality of the country’s entrepreneurial dynamic.

IV. Country-Level Digital Framework Conditions and Individual-Level Entrepreneurship Dynamics: Some Empirical Evidence

We draw on several datasets for the current study. As explained above, we use publicly available data from the GEM dataset for data on entrepreneurial attitudes, activities, and aspirations by individuals in select member economies of ADB (Reynolds et al. 2005). We use GEM data for all ADB member economies for which this data is available for any or all of the years 2010 – 2019, and for which sufficient data is also available to characterise the country's DFC for entrepreneurship. In total, 14 ADB member economies met these criteria.

For the empirical analysis, our GEM dataset covers a total of 190,515 (unweighted) interviews among working-age individuals (16–65 years old) for the following 14 ADB member economies: Bangladesh, China, Georgia, India, Indonesia, Kazakhstan, Malaysia, Pakistan, the Philippines, Singapore, the Republic of Korea, Thailand, Armenia, and Viet Nam. The sizes of the country samples per year are shown in Table 7.

Table 7: ADB Economy-Year Samples in the Dataset

ADB Economies	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	%of Total
Malaysia	2,010	2,053	2,006	2,000	2,000	2,000	2,005	2,033			**16,107**	8.5
Indonesia				4,500	5,520	5,620	3,480	2,500	3,090		**24,710**	13.0
Philippines				2,500	2,000	2,000					**6,500**	3.4
Singapore		2,000	2,001	2,000	2,006						**8,007**	4.2
Thailand		2,000	3,000	2,362	2,059	3,000	3,000	2,000	2,060		**19,481**	10.2
Korea, Republic of	2,001	2,001	2,000	2,000		2,000	2,000	2,000	2,000	2,000	**18,002**	9.4
Viet Nam				2,000	2,000	2,000		2,118			**8,118**	4.3
China, People's Republic of	3,677	3,690	3,684	3,634	3,647	3,822	3,974	3,911	3,828	3,841	**37,708**	19.8
India			2,700	3,000	3,360	3,413	3,400	4,000	4,165	3,398	**27,436**	14.4
Pakistan	2,007	2,002	2,000							2,000	**8,009**	4.2
Armenia										2,000	**2,000**	1.0
Kazakhstan					2,099	2,106	2,100	2,100			**8,405**	4.4
Bangladesh		2,000									**2,000**	1.0
Georgia					2,016		2,016				**4,032**	2.1
Total	**9,695**	**15,746**	**17,391**	**23,996**	**26,707**	**25,961**	**21,975**	**20,662**	**15,143**	**13,239**	**190,515**	100.0

Source: Authors

In our analysis, we pooled the data for each country, thereby achieving a sample that was clustered across 14 countries. Table 8 shows the numbers of baby businesses in each pooled country sample.

Table 8: Numbers of Baby Businesses in the Country Samples

ADB economies	**Baby Businesses**	**% of total**
China, People's Republic of	2,884	21.3
Indonesia	2,773	20.5
Thailand	2,159	16.0
Viet Nam	1,146	8.5
India	1,130	8.4
Korea, Republic of	970	7.2
Philippines	623	4.6
Malaysia	609	4.5
Kazakhstan	328	2.4
Singapore	307	2.3
Pakistan	195	1.4
Armenia	144	1.1
Bangladesh	133	1.0
Georgia	131	1.0
Total	**13,532**	100.0

Source: Authors

For the analysis, the individual-level GEM data on entrepreneurial activities was combined with other data sources such as the country-level institutional conditions, population and GDP data from the World Bank and the country-level digital condition data from the Asian Index of Digital Entrepreneurship Systems (AIDES). The AIDES index is a composite index that captures rich data on countries' DFCs. Detailed data on AIDES data sources and methodology is provided in the Appendix.

A. Dependent Variables

To assess the impact of country's DFCs on the quality of its entrepreneurial dynamic, we used three dependent variables which were measured using the GEM data.

Export orientation *was* measured by a dummy variable which took value "1" if the entrepreneurial business had *any* customers living outside of the country, and "0" otherwise.

High-growth expectation was measured by a dummy variable which took value "1" if the entrepreneurial business expected to employ at least 20 employees in 5 years' time and "0" otherwise.

New product introduction was measured by a dummy variable which took value “1” if at least some customers of the entrepreneurial business considered the firm’s product or service to be new to them and “0” otherwise.

B. Independent Variables

We adopted three alternative measures to capture the **Digital Framework Conditions** of the country. All three variables were measured using the data from the AIDES 2021. AIDES is a composite indicator that captures the quality of the country’s DFCs for entrepreneurship. The three main independent variables are:

AIDES score is the average of both general and systemic framework conditions. General framework conditions consist of four pillars: culture and informal institutions;[5] formal institutions, regulation, and taxation[6], market conditions[7] and physical infrastructure[8]. Systemic framework conditions are the resource-related conditions with a direct effect on the entrepreneurial dynamic. It consists of four pillars: human capital[9], knowledge creation and dissemination[10], finance[11], and networking and support[12] which are assessed at three different stages of entrepreneurship development: the stand-up, start-up, and scale-up stages.

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[5] Culture and Informal Institutions pillar consists of the following indicators: The efficiency of the legal framework in setting disputes, Corruption Perception Index, corporate governance, attitudes towards entrepreneurial risk, reliance on professional management, and willingness to delegate authority.

[6] Formal Institutions, Regulation and Taxation pillar consists of the following indicators: property rights, judicial effectiveness, distortive effect of taxes and subsidies on competition, total tax rate (reciprocal), and the efficiency of legal framework in challenging regulations

[7] Market Conditions pillar consists of the following indicators: the size of domestic market, urbanisation, extent of market dominance, economic complexity (re-scaled), and the prevalence of non-tariff barriers.

[8] Physical Infrastructure pillar consists of the following indicators: electricity infrastructure and transportation infrastructure.

[9] Human Capital pillar consists of two indicators at the stand-up stage: The quality of education and future workforce; four indicators at the start-up stage: tertiary education enrollment, percentage of universities in top ranking, science, technology, engineering, and mathematics education and researchers in R&D (per million people); three indicators at the scale-up stage: the extent of staff training, skilled labour, and labour freedom.

[10] Knowledge Creation and Dissemination pillar consists of three indicators at the stand-up stage: The skillset of graduates, percentage of professionals and researchers, and country’s capacity to attract and retain talents; three indicators at the start-up stage: the quality of research institutions, technicians and associate professionals, the quality of math and science in education; four indicators at the scale-up stage: the gross domestic expenditure on R&D, PCT patent applications, knowledge absorption, and university-industry collaboration in R&D.

[11] Finance pillar consists of two indicators at the stand-up stage: domestic credit to private sector as % of GDP and small and medium-sized enterprise access to finance; three indicators at the start-up stage: venture capital availability, venture capital funding, and number of VC investors; two indicators at the scale-up stage: market capitalization and financing through local equity market.

[12] It is measured by the score on the Social Capital at the stand-up stage, which assesses social cohesion and engagement, community and family networks, and political participation and institutional trust; two indicators at the start-up stage: international co-inventions and joint venture/strategic alliance deals; three indicators at the scale-up stage: the state of cluster development, multi-stakeholder collaboration, and logistic index.

Digital Ecosystem Score measures the effect of digital conditions (digitalization) for each country. It includes the DFCs, which consists of four pillars: culture, informal institutions (DFC_P1); formal institutions, regulation, taxation (DFC_P2); market conditions (DFC_P3); and systemic digital conditions (SDC) which consist of the following four pillars: human capital (SDC_P1); knowledge creation and dissemination (SDC_P2); finance (SDC_P3); networking and support (SDC_P4).

Digital Conditions (DC) is the part of the digital ecosystem. As described above, it consists of the following four pillars: culture, informal institutions (DFC_P1)[13]; formal institutions, regulation, taxation (DFC_P2)[14]; market conditions (DFC_P3)[15]; physical infrastructure (DFC_P4)[16].

a. Control Variables

We used both individual-level and country-level control variables. As individual-level control variables, we controlled for the entrepreneur's demographic characteristics. These included the individual's ***age*** measured in years; ***gender*** was coded as a dummy variable, with a value of 1 for male and 2 for female; ***household income*** was measured by a categorical variable with 3 categories which took the values of 1, 2, and 3 respectively, for lowest, middle-, and highest-income tiers in the population. The level of ***education*** was also captured by a categorical variable with the values 1, 2, 3, 4, and 5, indicating an individual had received no education, primary education, secondary degree, post-secondary education, and graduate education, respectively. The ***fear of failure*** indicated whether fear of failure would prevent the individual from starting up a business. It took value 1 if the individual replied yes to the question, and 0 otherwise. The ***entrepreneurial self-efficacy*** was captured by a dummy variable indicating that the individual believed that they possessed the required skills and knowledge to start a new business (yes = 1).

At the economy level, we controlled for the country's institutional conditions that may affect entrepreneurial dynamics. The variables included ***entry regulations*** which were captured by three

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[13] Networking and Support pillar is an aggregate measure of the following indictors: Percentage of households with a computer at home, percentage of households with Internet access, percentage of individuals using Internet, and percentage of firms having its own website.
[14] It is an aggregate measure of the following indictors: Percentage of network attacks by Kaspersky, the percentage of WEB treats, software piracy rate, the score of competition in network services, future orientation of government and E-government.
[15] It is an aggregate measure of the following indictors: Percentage of respondents who used the internet to pay bills or to buy something online in the past year, percentage of respondents used the internet to buy something online in the past year; the score of Internet shopping; percentage of firms that are using email to interact with clients/suppliers, the score of B2C E-commerce Index, and the market share of each country in relation to global e-commerce (T-index).
[16] It is an aggregate measure of the following indictors: the prepaid mobile cellular tariffs; data-only mobile-broadband basket (1.5 GB and above); fixed broadband Internet tariffs; fixed broadband 5GB, median download speed, median upload speed, mobile network coverage, and secure Internet servers.

variables. First, the number of procedures required to register a new business proxied the difficulty of launching a new business in the country. Second, the cost of new business registration (as percentage of GDP per capita purchasing power parity [PPP]) measured the cost of new firm registration process. Third, the required minimum paid-in capital for new business registration (as percentage of GDP per capita PPP) measured the financial capital requirement of new business registration. All three measures were taken from the World Bank's Doing Business database (Djankov, La Porta, Lopez-de-Silanes, and Shleifer 2002b). Another institutional condition was the level of ***financial development*** of a country. It measured based on the International Monetary Fund's Financial Development Indicator Database. This is an aggregate index that consists of nine indices that assess the development of the country's financial institutions and financial markets along three dimensions: depth (size and liquidity), access (ability of individuals and firms to access financial services), and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues, and the level of activity of capital markets). These indices are then aggregated into an overall index of financial development (Svirydzenka 2016). The index ranges from 0 to 1, with higher values indicating higher levels of financial development.

We also controlled for country's ***population size*** and ***population growth,*** measured by the total number of population of a country (in millions) and the population's annual growth rate. The ***GDP per capita,*** adjusted for Purchasing Power Parity (PPP), and ***GDP growth*** were measured using annual GDP growth rate of the ADB member economies based on the World Bank data. We also controlled for the fixed effects of time by including the ***year*** dummies in the analysis.

b. Method

We conducted cross-level analyses of country-level effects on individual-level entrepreneurial behaviors to estimate the effect of country-level DFCs on the quality of the country's entrepreneurial dynamic at the individual level. Because of the nested nature of our dataset (individuals were nested within each ADB country), we adopted multilevel modelling techniques to estimate the proposed relationships.

Before conducting the analysis, we investigated potential sample selection issues. Our analysis focuses on high-quality entrepreneurs and their businesses that possess high productivity potential. High-potential entrepreneurs are defined as those who introduce product and service innovations, engage in export activity, and aspire for high employment growth. These attributes can only be observed for those individuals who self-select as new entrepreneurs. It is possible that there might be unobserved attributes that first prompt the individual to pursue entrepreneurial opportunities and subsequently drive high-quality entrepreneurial outcomes after entry. The presence of potential unobserved

heterogeneity might obscure the effect of DFCs on the quality of entrepreneurial businesses at the individual level. To control for potential bias resulting from unobserved heterogeneity, we adopted a two-stage Heckman selection model (Heckman 1979). In the first stage, we estimated the probability that a given individual self-selects as an early-stage entrepreneur in the dataset. This first step was estimated as a function of the individual's gender, age, household income, education, fear of failure, familiarity ties with other entrepreneurs, entrepreneurial self-efficacy, as well as country-level population size, population growth, GDP per capita, GDP growth and the key institutional variables about entry regulations, financial development, and digital framework conditions (Table 9). In the second stage of the Heckman model, we used the error residual (referred to as the Inverse Mills ratio) of the first-stage estimation to control for unobserved heterogeneity when estimating the impact of DFCs on the quality of entrepreneurial businesses on the condition that an individual had identified as an early-stage entrepreneur in the sample), in addition to the controls for age, gender, education, household income, fear of failure, rate of established businesses, GDP per capita, GDP growth, population size. To facilitate model dentification, familiarity ties with other entrepreneurs was excluded from the second-stage outcome model. This step eliminated the possible effect of any self-selection bias in our analysis.

Table 9: First-Stage Selection Model

	Selection Model
VARIABLES	Total Early-Stage
AIDES	0.003
	(0.006)
Gender (Male=1, Female=0)	0.046+
	(0.024)
Age	-0.003***
	(0.001)
Income1 (Middle 33% tier)	0.015
	(0.020)
Income2 (Upper 33% tier)	0.137***
	(0.023)
Education1 (some secondary)	0.043
	(0.032)
Education2 (secondary)	0.025
	(0.032)
Education3 (post-secondary)	-0.004
	(0.034)
Education4 (graduate experience)	-0.017
	(0.054)
Fear of Failure (yes=1)	-0.082**
	(0.026)
Self-efficacy (yes=1)	0.677***
	(0.027)
Acquaintance with other entrepreneurs	0.450***
	(0.021)
Population size	-0.064*
	(0.027)
Population growth (%)	-0.230+
	(0.130)
GDP development stage (2nd quintile)	0.033
	(0.098)
GDP development stage (3rd quintile)	-0.130
	(0.120)
GDP development stage (4th quintile)	-0.113
	(0.134)
GDP development stage (5th quintile)	-0.188
	(0.131)
GDP growth (%)	-0.019
	(0.025)
Number of Procedures	0.050*
	(0.020)
Registration Cost (% per capita income)	-0.014**
	(0.005)
Paid-in Minimum Capital (% per capita income)	0.000
	(0.001)
Financial Development	0.304
	(0.482)
Year dummies	Yes
Constant	-1.769***
	(0.254)
Observations	154,839
Number of groups	71
Pseudo-R2	0.241
Log likelihood	-54062.176
Degrees of Freedom	32
Wald chi2	1573.45

AIDES= Asian Index of Entrepreneurial Sytems, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10
Note: Standard errors in parentheses
Source: Authors.

We specified and tested a set of two-level models with random intercepts, which allowed both the individual-level factors (level-1) and country-level factors (level-2) to affect the likelihood of product innovation, export activity, and employment growth aspirations of individual entrepreneurs, accounting for variation in these outcomes across countries. We used maximum likelihood algorithms to fit the models. In the regression models, the continuous independent variables were all standardized to have a mean of zero and a standard deviation of 1 to increase comparability of the estimated coefficients.

c. Results: The Effect of Country-Level Digital Framework Conditions on the Quality of Individual-Level Entrepreneurial Businesses

Tables from A1 to A6 (refer to the Appendix 1) present the descriptive statistics and correlations for all variables included in the models to predict export orientation, high-growth orientation, and new product innovation in baby businesses in the 14 ADB member economies included in the analysis. There was no concern of multicollinearity among independent variables in the regression analyses. The high levels of correlation between alternative explanatory variables which capture country's DFCs are expected. These explanatory variables entered the regression models and were tested separately.

Table 10 shows the associations between a country's DFCs and the export orientation of its baby businesses. We can see that the country-level AIDES index digital ecosystem, and digital conditions were not associated with the likelihood of exporting activity among baby businesses.

Table 11 shows associations between a country's DFCs and high-growth expectations among its baby businesses. As we can see from Table 11, the country-level AIDES index (0.508, p-value <0.05), Digital Ecosystem score (0.432, p-value <0.05), and Digital Condition (0.591, p-value <0.05) are positively associated with the likelihood of baby entrepreneurial businesses exhibiting high-growth expectations.

Table 10: Effects of Digital Framework Conditions on Export Orientation of Baby Business

VARIABLES	Model1	Model2	Model3
AIDES	0.169		
	(0.212)		
Digital Ecosystem		0.043	
		(0.212)	
Digital Condition (DC)			0.014
			(0.233)
Gender (Male=1, Female=0)	-0.015	-0.016	-0.016
	(0.081)	(0.081)	(0.081)
Age	-0.010	-0.009	-0.009
	(0.031)	(0.031)	(0.031)
Income1 (Middle 33% tier)	-0.140	-0.139	-0.140
	(0.109)	(0.109)	(0.109)
Income2 (Upper 33% tier)	0.264*	0.264*	0.264*
	(0.132)	(0.132)	(0.132)
Education1 (some secondary)	-0.185	-0.183	-0.183
	(0.187)	(0.186)	(0.186)
Education2 (secondary)	0.012	0.015	0.016
	(0.216)	(0.215)	(0.215)
Education3 (post-secondary)	0.328	0.331	0.332
	(0.219)	(0.218)	(0.218)
Education4 (graduate experience)	0.556*	0.561*	0.563*
	(0.280)	(0.280)	(0.280)
Fear of Failure (yes=1)	-0.022	-0.022	-0.022
	(0.097)	(0.097)	(0.097)
Business rate	-	-	-
	(0.124)	(0.119)	(0.122)
Population size	-0.441*	-0.486**	-0.495**
	(0.184)	(0.178)	(0.182)
Population growth (%)	0.098	0.156	0.161
	(0.178)	(0.181)	(0.197)
GDP development stage (2nd quintile)	-0.634+	-0.643+	-0.645+
	(0.363)	(0.358)	(0.359)
GDP development stage (3rd quintile)	-	-	-
	(0.315)	(0.308)	(0.311)
GDP development stage (4th quintile)	-	-	-
	(0.380)	(0.383)	(0.392)
GDP development stage (5th quintile)	-	-	-
	(0.517)	(0.535)	(0.542)
GDP growth (%)	0.035	0.061	0.066
	(0.099)	(0.096)	(0.094)
Number of Procedures	0.391+	0.347	0.338
	(0.237)	(0.226)	(0.218)
Registration Cost (% per capita income)	-	-	-
	(0.121)	(0.124)	(0.145)
Paid-in Minimum Capital (% per capita	0.118	0.153	0.158
	(0.119)	(0.116)	(0.117)
Financial Development	0.552*	0.687**	0.711***
	(0.258)	(0.211)	(0.191)
Year dummies (2019 as the baseline)	Yes	Yes	Yes
Inverse Mills Ratio	0.211	0.211	0.211
	(0.160)	(0.160)	(0.160)
Constant	2.107**	2.133**	2.131**
	(0.666)	(0.665)	(0.666)
Observations	11,636	11,636	11,636
Number of groups	71	71	71
Pseudo-R2	0.404	0.405	0.405
Log likelihood	-4947.48	-4947.88	-4947.91
Degrees of Freedom	32	32	32
Wald chi2	289.92	284.64	283

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.
Note: Standard errors in parentheses.
Source: Authors.

Note that the coefficients in logistic regressions are in the form of log odds. That is, regression coefficients imply that one-unit increase in an independent variable would be associated with the amount of change in the log of the odds ratio indicated by the coefficient, i.e., log(p/1-p) or logit(p). P is the probability of "success" (dependent variable takes value 1), such as an entrepreneurial venture engaging in exporting activities, or being innovative, or exhibiting high-growth aspirations. (1-p) is the probability of failing to do so (dependent variable takes value 0). For example, the coefficient of AIDES index 0.508 in Model 1 of Table 11 means that a one-standard deviation increase in the AIDES index would be associated with 0.508 change in the log of the odds ratio.

The result can be understood better in terms of percentage change. We can say that one standard-deviation increase in AIDES index was associated with about 66.2% increase in the odds of a given baby business in the sample with high-growth expectations, as the change in odds ratio (i.e., OR), is 1.662 obtained by expatiating of the log odds, i.e., exp (0.508) = 1.662. OR values greater than 1 indicate positive associations, and values smaller than 1 signal negative associations. Similarly, we can say that a one standard-deviation increase in the Digital Ecosystem score was associated with 54% (i.e., exp (0.432) = 1.54) increase in the odds of a baby business in the sample exhibiting high growth expectations. In comparison with the AIDES index and digital ecosystem score, the digital condition score exhibited a stronger association with the high-growth expectations of baby businesses. The increases in the odds of having high-growth expectations are 80.6% (i.e., exp (0.591) = 1.806) for baby businesses.

To show the effects in the form of probability is not straightforward. This is because in the probability scale, all effects are non-linear and conditional on all covariate values in the model (Wiersema and Bowen 2009). We report the marginal effect of the key explanatory variables, keeping other variables at their sample mean value (Table 13). We can see that for a one standard-deviation increase in AIDES index, the likelihood of a baby business exhibiting high-growth expectations increased by 1.8 percentage points – i.e., the average marginal effect was 0.018 ($p<0.05$). A one standard-deviation increase in the Digital Ecosystem score was positively associated with an increase in the likelihood of high-growth expectations in baby businesses by 1.5% (0.015, $p<0.1$). The digital condition of a country showed a slightly stronger marginal effect than the other two variables, for which one standard-deviation increase was associated with a 2% increase in the likelihood of a baby business exhibiting high-growth expectations.

Table 11: Effects of Digital Framework Conditions on High-growth Expectations of Baby Businesses

VARIABLES	Model1	Model2	Model3
AIDES	0.508*		
	(0.220)		
Digital Ecosystem		0.432*	
		(0.213)	
Digital Condition (DC)			0.591*
			(0.242)
Gender (Male=1, Female=0)	0.484***	0.486***	0.488***
	(0.109)	(0.109)	(0.109)
Age	0.073	0.072	0.070
	(0.051)	(0.051)	(0.051)
Income1 (Middle 33% tier)	0.027	0.032	0.035
	(0.175)	(0.174)	(0.174)
Income2 (Upper 33% tier)	0.204	0.207	0.209
	(0.179)	(0.178)	(0.178)
Education1 (some secondary)	-0.162	-0.166	-0.173
	(0.309)	(0.311)	(0.312)
Education2 (secondary)	0.081	0.075	0.064
	(0.340)	(0.344)	(0.346)
Education3 (post-secondary)	0.804*	0.797*	0.784*
	(0.345)	(0.349)	(0.352)
Education4 (graduate experience)	1.516***	1.519***	1.511***
	(0.442)	(0.442)	(0.441)
Fear of Failure (yes=1)	0.095	0.097	0.100
	(0.147)	(0.147)	(0.147)
Business rate	-0.095	-0.138	-0.096
	(0.191)	(0.188)	(0.185)
Population size	0.542*	0.461*	0.336
	(0.241)	(0.231)	(0.229)
Population growth (%)	-0.390*	-0.230+	-0.135
	(0.172)	(0.139)	(0.136)
GDP development stage (2nd quintile)	-0.237	-0.261	-0.222
	(0.577)	(0.572)	(0.541)
GDP development stage (3rd quintile)	-1.101+	-1.127+	-1.015+
	(0.582)	(0.580)	(0.604)
GDP development stage (4th quintile)	0.259	0.177	0.276
	(0.615)	(0.628)	(0.633)
GDP development stage (5th quintile)	1.506*	1.166+	1.079+
	(0.660)	(0.618)	(0.609)
GDP growth (%)	-0.067	-0.027	-0.003
	(0.167)	(0.166)	(0.165)
Number of Procedures	0.247	0.207	0.239
	(0.343)	(0.345)	(0.326)
Registration Cost (% per capita income)	-	-	-
	(0.201)	(0.202)	(0.205)
Paid-in Minimum Capital (% per capita	-0.207	-0.151	-0.154
	(0.224)	(0.219)	(0.223)
Financial Development	-0.806*	-0.587*	-0.570*
	(0.333)	(0.262)	(0.233)
Year dummies (2019 as the baseline)	Yes	Yes	Yes
Inverse Mills Ratio	0.636**	0.633**	0.634**
	(0.235)	(0.235)	(0.235)
Constant	-	-	-
	(0.654)	(0.657)	(0.667)
Observations	12,432	12,432	12,432
Number of groups	71	71	71
Pseudo-R2	0.436	0.439	0.443
Log likelihood	-1707.27	-1707.76	-1706.61
Degrees of Freedom	32	32	32
Wald chi2	454.58	435.65	428.17

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Note: Standard errors in parentheses.

Source: Authors.

Regarding entrepreneurs' innovation activities, we explored associations between a country's digital conditions and its entrepreneurs' propensity of introducing new products and services. As shown in Table 12 country-level AIDES index (0.381, p-value <0.01), digital ecosystem (0.387, p-value <0.01), and digital condition (0.474, p-value <0.001;) exhibited strong and consistent positively associations with the likelihood of product innovation by baby businesses.

The marginal effects of the three alternative explanatory variables are shown in Table 13. We can see that for a one standard-deviation increase in AIDES index, the likelihood of the baby business engaging in product innovation increased by 8.2 percentage points – i.e., the average marginal effect was 0.082 (p<0.001). A one standard-deviation increase in the digital ecosystem score was positively associated with an increase in the likelihood of product innovation by baby businesses by 8.3%. The strongest average marginal effect was found in the digital condition of a country, for which one standard-deviation increase was associated with an over 10% increase in the likelihood of product innovation in baby businesses.

Table 12: Effects of Digital Framework Conditions on New Product introduction of Baby Businesses

VARIABLES	Model1	Model2	Model3
AIDES	0.381**		
	(0.122)		
Digital Ecosystem		0.387**	
		(0.126)	
Digital Condition (DC)			0.474**
			(0.144)
Gender (Male=1, Female=0)	0.021	0.022	0.022
	(0.050)	(0.050)	(0.050)
Age	-0.067**	-0.069**	-0.069**
	(0.022)	(0.022)	(0.022)
Income1 (Middle 33% tier)	-0.025	-0.024	-0.022
	(0.096)	(0.096)	(0.096)
Income2 (Upper 33% tier)	0.091	0.091	0.091
	(0.108)	(0.108)	(0.108)
Education1 (some secondary)	-0.014	-0.017	-0.018
	(0.095)	(0.095)	(0.095)
Education2 (secondary)	0.177+	0.172+	0.169+
	(0.096)	(0.096)	(0.096)
Education3 (post-secondary)	0.440**	0.433**	0.429**
	(0.104)	(0.105)	(0.105)
Education4 (graduate experience)	0.952**	0.955**	0.957**
	(0.179)	(0.179)	(0.179)
Fear of Failure (yes=1)	0.166*	0.167*	0.168*
	(0.068)	(0.068)	(0.068)
Business rate	-0.052	-0.064	-0.036
	(0.085)	(0.083)	(0.083)
Population size	0.454**	0.415**	0.328*
	(0.149)	(0.140)	(0.135)
Population growth (%)	-0.279*	-0.174+	-0.091
	(0.109)	(0.092)	(0.093)
GDP development stage (2nd quintile)	-0.319	-0.317	-0.276
	(0.224)	(0.222)	(0.203)
GDP development stage (3rd quintile)	-0.410*	-0.416*	-0.259
	(0.185)	(0.190)	(0.194)
GDP development stage (4th quintile)	-0.367	-0.374	-0.281
	(0.264)	(0.277)	(0.287)
GDP development stage (5th quintile)	-0.416	-0.636*	-0.656*
	(0.322)	(0.312)	(0.309)
GDP growth (%)	-0.236*	-0.218*	-0.195*
	(0.095)	(0.092)	(0.090)
Number of Procedures	0.453**	0.441**	0.439**
	(0.139)	(0.128)	(0.108)
Registration Cost (% per capita income)	-0.180*	-0.179*	-0.110
	(0.075)	(0.073)	(0.079)
Paid-in Minimum Capital (% per capita	-0.019	0.006	0.000
	(0.090)	(0.086)	(0.088)
Financial Development	0.013	0.108	0.134
	(0.165)	(0.133)	(0.110)
Year dummies (2019 as the baseline)	Yes	Yes	Yes
Inverse Mills Ratio	0.413**	0.411**	0.412**
	(0.096)	(0.096)	(0.096)
Constant	-0.796+	-0.700+	-0.693+
	(0.412)	(0.399)	(0.407)
Observations	11,741	11,741	11,741
Number of groups	71	71	71
Pseudo-R2	0.190	0.190	0.191
Log likelihood	-7292.09	-7291.13	-7289.19
Degrees of Freedom	32	32	32
Wald chi2	457.17	465.08	480.22

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.
Note: Standard errors in parentheses.
Source: Authors.

Table 13: Average Marginal Effects of Digital Conditions on High-quality Entrepreneurship

High-growth expectation of baby businesses	Average Marginal Effects	Std. Err.
AIDES	0.018*	0.008
Digital Ecosystem	0.015+	0.008
Digital Framework Condition (DFC)	0.02*	0.009
New Product Introduction of baby businesses	**Average Marginal Effects**	**Std. Err.**
AIDES	0.082***	0.026
Digital Ecosystem	0.083**	0.027
Digital Condition (DC)	0.101***	0.03

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Std. Err = standard error, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.
Source: Authors.

V. Discussion and Conclusions

In this report we set out to explore potential effects of a country's DFCs on the quality and productivity potential of the country's entrepreneurial dynamic in 14 ADB member economies. Our analysis was based on three important premises: (i) drawing on reasoning in received literature, we expected that individual-level entrepreneurial activity in a country should have an important potential impact on the country's TFP because it has the potential to allocate human and social capital and other valuable resources towards high-productivity uses; (ii) this effect may not be automatic, given the high degree of heterogeneity among entrepreneurial businesses in terms of their productivity potential; and (iii) a country's prevailing framework conditions for entrepreneurship (such as its DFCs) should regulate the productivity potential of the country's entrepreneurial dynamic by shaping the occupational trade-offs that individuals experience when faced with entrepreneurial opportunities.

Our descriptive analysis using GEM data from years 2010–2019 for 17 ADB member economies confirmed these premises by highlighting the extreme heterogeneity of these economies' populations of entrepreneurial businesses particularly when it came to the employment growth potential: whereas entrepreneurial businesses experiencing very rapid employment growth (i.e., reaching employment size of 250 or higher) represented only 0.4% of all entrepreneurial businesses, they nevertheless generated nearly half of all new jobs created by them. On the other hand, micro businesses that employed up to two people represented about 50% of all entrepreneurial businesses, yet they created less than 10% of all new jobs created by entrepreneurial businesses. Similar heterogeneity was also exhibited for export activity, with at least three quarters of all new entrepreneurial businesses reporting no exports and only a small minority reporting significant export activity (defined in terms of the firm having customers outside its home country). For product and service innovation, the biases were less pronounced, yet quite clear.

Our descriptive analysis suggests that "one size fits all" policies to support entrepreneurship might not be very effective in maximising the productivity potential of a country's entrepreneurial dynamic. Instead, governments might expect better success by shaping the country's framework conditions for entrepreneurship such that they present a more favorable trade-offs for high-potential individuals when these are considering whether to allocate their human, social, financial, and other valuable resources towards the pursuit of entrepreneurial opportunities over alternative occupational choices. Focusing specifically on the country's DFC for entrepreneurship, we hypothesised five mechanisms through which high-quality DFCs should be able to tilt this trade-off in favor of an entrepreneurial career for high-

potential individuals (i.e., those possessing valuable human, social, financial, and other capital and resources that can be allocated to pursue entrepreneurial opportunities): (i) digital commons reduce the need of entrepreneurs to invest in physical resources, thereby lowering the cost of entrepreneurial opportunity pursuit; (ii) digital technologies enable more effective coordination and outsourcing of activities, thereby boosting opportunities to compete with disruptive business models; (iii) digital infrastructures reduce the cost of and barriers to scaling in general and international scaling in particular; (iv) digital technologies are able to effectively support extensive outsourcing of activities, thereby enabling high-potential entrepreneurs to focus on their core competencies and thus achieve distinctive advantages more rapidly and at lower cost; and (v) digital technologies support cost-efficient experimentation with different value offerings, enabling entrepreneurs to more easily discover innovative value offerings that customers are likely to value. We theorized that all these mechanisms should be able to support the quality of the country's entrepreneurial resource allocation dynamic, as expressed in the employment growth orientation, export orientation, and product and service innovation of the country's entrepreneurial businesses.

Our multilevel analysis showed consistent support for the positive association between the quality of the country's DFCs and the export orientation and employment growth orientation of its entrepreneurial businesses: countries with stronger DFCs saw entrepreneurial businesses that had more customers in other countries, and they also had more established entrepreneurs who aspired to grow their number of employees more rapidly. These effects were quite strong, even when using appropriate methods to eliminate potential selection bias: one standard-deviation increase in the quality of the country's DFCs increased the probability of its entrepreneurial baby businesses introducing product innovation by 10%. For employment growth expectations, we observed a significant association between the country's DFCs for baby entrepreneurial businesses as expected. However, contrary to theory-informed expectation, our data did not show a positive association between the quality of a country's DFCs and the export activities of entrepreneurial businesses.

Summarizing, our analysis has revealed quite significant and positive associations between the quality of the country's DFCs and the productivity potential of its entrepreneurial businesses in a set of ADB member economies. We are not aware of any previous studies who would have explored this particular effect. Given the transformative impact that digital technologies and infrastructures are exercising on the organisation of economic activity, the evidence reported here suggests that this question merits further attention. We believe these findings signal a potentially important link between entrepreneurship and

digitalisation policies in ADB member economies, given that digitalisation is an urgent concern for many of these. Our analysis suggests that ADB member economies could achieve important gains by investing in their digital infrastructures, not only because of the many direct effects these are likely to have on the countries' economies, but also, because such investments appear able to enhance the productivity potential of their entrepreneurial sectors.

A limitation of this study is that country-level DFCs tend to be strongly correlated: a country that exhibits strong digital capabilities on one aspect will likely do so in others too. Because of this collinearity, our statistical models have not been able to test how the different DFCs would behave when entered into the regression equations simultaneously. Similarly, countries with strong DFCs also tend to exhibit strengths in terms of other institutional and physical framework conditions such as rule of law, institutional quality, and physical infrastructure. This makes it difficult to separate the effect of digital framework conditions from other framework conditions. Although we do control the country's GDP per capita, which captures the effect of the country's general wealth, a richer and larger dataset could help bring out more nuance. Finally, we note that the statistical associations could be because of at least two different reasons: selection effects and through their effect on the ability of entrepreneurial businesses to grow and innovate. The first effect operates through the self-selection of individuals with high human and social capital to entrepreneurship – high-quality EFCs would attract more high-potential individuals to start new businesses. The second effect operates through the ability of strong DFCs to support growth and innovation in entrepreneurial businesses of all kinds. More research is required to address this question.

Regardless of these limitations, our findings suggest several policy implications. We add to the already substantial body of evidence that strong DFCs have a positive effect on economic growth and development – in our case, this effect would operate through the quality of the country's entrepreneurial resource allocation dynamic. Therefore, governments in ADB member economies would be well advised to invest in their digital infrastructures – notably, on their coverage, capacity, openness, and accessibility. Policies to bridge the digital divide are important, as they allow more entrepreneurs to integrate digital technologies into their offerings and operations. Promoting competition among alternative providers of digital infrastructure and telecommunication services is important to promote coverage, openness, and accessibility of digital and telecommuni-cation infrastructures at competitive price. It is important to extend the reach of telecommunication networks to rural areas also as widely as possible to enable rural entrepreneurs also to connect and access the benefits of these. Alongside with strengthening the country's DFCs, it is also important to strengthen digital literacy and capabilities of existing and prospective

entrepreneurs so they are better able to take advantage of emerging opportunities. An effective way of accomplishing this is by promoting regional entrepreneurial ecosystems, or regional communities of entrepreneurs, new venture accelerators, co-working spaces, advisors, and investors, as such communities provide an effective environment for sharing knowledge and insights regarding emerging digital opportunities and how to best exploit them. Even today, policies for small and medium-sized enterprises in many countries are biased towards traditional forms of support, such as loans and investment subsidies. To take advantage of digital advances, countries should adopt explicit policies to promote regional entrepreneurial ecosystems and effectively coordinate their entrepreneurship policy with digitalization policy.

Appendix 1 Statistical Analyses

Table A1 Descriptive Statistics for Entrepreneurs' Export Activity Analysis

Variable	Observation	Mean	Std. Dev.	Min	Max
Export	11,636	0.23	0.42	0	1
AIDES	11,636	28.78	12.11	12.33	81.29
Digital Ecosystem	11,636	0.46	0.11	0.27	0.83
Digital Condition	11,636	0.45	0.13	0.28	0.75
Gender (Male=1, Female=0)	11,636	0.52	0.50	0	1
Age	11,636	37.23	11.09	18	64
Household Income	11,636	2.14	0.82	1	3
Education	11,636	2.99	1.00	1	5
Fear of Failure (yes=1)	11,636	0.40	0.49	0.00	1.00
Business Rate (%)	11,636	0.29	0.11	0.05	0.51
Population Size (millions)	11,636	455.62	547.55	2.96	1397.715
Population Growth (%)	11,636	0.91	0.46	0.05	2.45
GDP development stage	11,636	2.96	1.40	1	5
GDP Growth (%)	11,636	5.58	2.08	0.84	10.64
Number of Procedures	11,636	9.88	3.46	2	17.00
Registration Cost (% per capita income)	11,636	11.74	8.66	0.30	43.73
Paid-in Minimum Capital (% per capita income)	11,636	24.36	39.03	0	149.62
Financial Development	11,636	0.51	0.17	0.20	0.84
Year	11,636	2014.34	2.17	2010	2019

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Max = maximum, Min = minimum, Std. Dev. = standard deviation.
Source: Authors.

Table A2 Correlations of Variables (Export of Baby Businesses)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Export	1																			
2 AIDES	0.21*	1																		
3 Digital Ecosystem	0.19*	0.98*	1																	
4 Digital Condition	0.19*	0.89*	0.95*	1																
5 Gender (Male=1, Female=0)	0.03*	0.06*	0.06*	0.05*	1															
6 Age	-	0.10*	0.10*	0.08*	0	1														
7 Household Income	0.11*	0.08*	0.09*	0.12*	0.08*	-	1													
8 Education	0.13*	0.19*	0.22*	0.21*	0.04*	-	0.31*	1												
9 Fear of Failure (yes=1)	-	-	-	-	-	0.02*	-	-	1											
10 Business Rate	-	-	-	-	-	-0.02	-	-	0.06*	1										
11 Population Size (millions)	-	-	-	-	0.02*	-	0.05*	-	-0.01	-	1									
12 Population Growth (%)	0.003	-	-	-	0.02	-	-	-	-	-	-	1								
13 GDP development stage (2nd quintile)	-	-	-	-	-	0.02*	-	-	-	0.12*	0.09*	0.12*	1							
14 GDP development stage (3rd quintile)	-	-	-	-	-	-	0.02*	-	-	0.03*	0.34*	0.07*	-	1						
15 GDP development stage (4th quintile)	-	0.04*	0.05*	0.15*	-	0.02*	0.03*	0.002	0.02	0.20*	0.07*	-	-	-	1					
16 GDP development stage (5th quintile)	0.18*	0.64*	0.63*	0.50*	0.06*	0.11*	0.01	0.15*	-	-	-	-0.01	-	-	-	1				
17 GDP Growth (%)	0.05*	-	-	0.11*	0.01	-	0.06*	-	-0.02	-	0.64*	0.03*	0.16*	0.18*	-	-	1			
18 Number of Procedures	-	-	-	-	-	-	-	-	-	-	0.57*	0.48*	0.17*	0.36*	-	-	0.48*	1		
19 Registration Cost	-	-	-	-	0.03*	-	-	-	-	-	0.05*	0.60*	0.23*	0.13*	-	-	-	0.57*	1	
20 Paid-in Minimum Capital	-	-0.01	-	0.08*	0.01	-	-0.01	-	-	0.02*	0.62*	-	0.12*	0.47*	-	-	0.58*	0.43*	0.11*	1
21 Financial Development	0.12*	0.67*	0.68*	0.69*	0.02*	0.13*	0.04*	0.13*	-	-	-	-	-	-	0.42*	0.55*	-	-	-	-

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Max = maximum, Min = minimum, Std. Dev. = standard deviation, * = Indicates correlation coefficients significant at 5% level or better.

Note: Number of observations: 11,636

Source: Authors.

Table A3 Descriptive Statistics for Entrepreneurs' High-growth Expectations Analysis

Variable	Observation	Mean	Std. Dev.	Min	Max
High-growth expectations	12,432	0.04	0.20	0	1
AIDES	12,432	28.81	12.17	12.33	81.29
Digital Ecosystem	12,432	0.46	0.11	0.27	0.83
Digital Condition	12,432	0.45	0.13	0.28	0.75
Gender (Male=1, Female=0)	12,432	0.53	0.50	0	1
Age	12,432	37.23	11.12	18	64
Household Income	12,432	2.14	0.82	1	3
Education	12,432	2.99	1.00	1	5
Fear of Failure (yes=1)	12,432	0.40	0.49	0	1
Business Rate	12,432	0.29	0.11	0.05	0.51
Population Size (millions)	12,432	467.66	555.30	2.96	1397.72
Population Growth (%)	12,432	0.90	0.47	0.05	2.45
GDP development stage	12,432	2.94	1.42	1	5
GDP Growth (%)	12,432	5.54	2.11	0.84	10.64
Number of Procedures	12,432	9.77	3.52	2	17
Registration Cost (% per capita income)	12,432	11.66	8.63	0.30	43.73
Paid-in Minimum Capital (% per capita income)	12,432	23.68	38.83	0	149.624
Financial Development	12,432	0.51	0.17	0.20	0.84
Year	12,432	2014.51	2.30	2010	2019

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Max = maximum, Min = minimum, Std. Dev. = standard deviation.

Source: Authors.

Table A4 Correlations of Variables (High-growth Expectations of Baby Businesses)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 High-growth expectations	1																			
2 AIDES	0.13*	1																		
3 Digital Ecosystem	0.13*	0.98*	1																	
4 Digital Condition	0.15*	0.90*	0.95*	1																
5 Gender (Male=1, Female=0)	0.06*	0.06*	0.05*	0.05*	1															
6 Age	-0.01	0.11*	0.11*	0.09*	0	1														
7 Household Income	0.08*	0.08*	0.09*	0.12*	0.08*	-	1													
8 Education	0.10*	0.20*	0.22*	0.22*	0.04*	-	0.31*	1												
9 Fear of Failure (yes=1)	-0.01	-	-	-	-	0.02	-	-	1											
10 Business Rate	-	-	-	-	-	-0.01	-	-	0.06*	1										
11 Population Size (millions)	0.02*	-	-	-	0.02*	-	0.05*	-	0.004	-	1									
12 Population Growth (%)	-	-	-	-	0.02	-	-	-	-	-	-	1								
13 GDP development stage (2nd quintile)	-	-	-	-	-	0.02*	-	-	-	0.12*	0.09*	0.11*	1							
14 GDP development stage (3rd quintile)	-	-	-	-	-	-	0.02*	-	-	0.03*	0.33*	0.06*	-	1						
15 GDP development stage (4th quintile)	0.05*	0.04*	0.04*	0.14*	-	0.02*	0.03*	0.001	0.01	0.21*	0.07*	-	-	-	1					
16 GDP development stage (5th quintile)	0.06*	0.65*	0.64*	0.51*	0.06*	0.11*	0.01	0.16*	-	-	-	-	-	-	-	1				
17 GDP Growth (%)	0.03*	-	-	0.09*	0.001	-	0.06*	-	-0.02	-	0.58*	0.01	0.16*	0.19*	-	-	1			
18 Number of Procedures	-	-	-	-	-	-	-	-	0.01	-	0.57*	0.50*	0.17*	0.34*	-	-	0.46*	1		
19 Registration Cost	-	-	-	-	0.03*	-	-	-	0.001	-	0.07*	0.58*	0.22*	0.11*	-	-	-	0.56*	1	
20 Paid-in Minimum Capital	-0.02	-0.01	-	0.08*	0.01	-	-	-	-	0.03*	0.59*	-	0.12*	0.47*	-	-	0.58*	0.43*	0.11*	1
21 Financial Development	0.08*	0.68*	0.69*	0.70*	0.02*	0.13*	0.03*	0.14*	-	-	-	-	-	-	0.41*	0.55*	-	-	-	-

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Max = maximum, Min = minimum, Std. Dev. = standard deviation, * = Indicates correlation coefficients significant at 5% level or better.

Note: Number of observations: 12,432.

Source: Authors.

Table A5 Descriptive Statistics for Entrepreneurs' Product Innovation Analysis

Variable	Observation	Mean	Std. Dev.	Min	Max
Product Innovation	11,741	0.51	0.50	0	1
AIDES	11,741	28.75	12.26	12.33	81.29
Digital Ecosystem	11,741	0.45	0.11	0.27	0.83
Digital Condition	11,741	0.45	0.13	0.28	0.75
Gender (Male=1, Female=0)	11,741	0.53	0.50	0	1
Age	11,741	37.21	11.12	18	64
Household Income	11,741	2.14	0.82	1	3
Education	11,741	3.00	1.00	1	5
Fear of Failure (yes=1)	11,741	0.40	0.49	0	1
Business Rate (%)	11,741	0.29	0.11	0.05	0.51
Population Size (millions)	11,741	452.60	#####	2.96	1397.72
Population Growth (%)	11,741	0.91	0.47	0.05	2.45
GDP development stage	11,741	2.94	1.43	1	5
GDP Growth (%)	11,741	5.51	2.09	0.84	10.6361
Number of Procedures	11,741	9.80	3.50	2	17
Registration Cost (% per capita income)	11,741	11.80	8.61	0.30	43.7305
Paid-in Minimum Capital (% per capita income)	11,741	23.08	38.32	0	149.624
Financial Development	11,741	0.51	0.17	0.20	0.84
Year	11,741	2014.47	2.25	2010	2019

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Max = maximum, Min = minimum, Std. Dev. = standard deviation.

Source: Authors.

Table A6 Correlations of Variables (Product Innovation of Baby Businesses)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Product innovation	1																			
2 AIDES	0.06*	1																		
3 Digital Ecosystem	0.07*	0.98*	1																	
4 Digital Condition	0.13*	0.90*	0.95*	1																
5 Gender (Male=1, Female=0)	0.003	0.06*	0.06*	0.05*	1															
6 Age	-	0.10*	0.11*	0.09*	-0.01	1														
7 Household Income	0.11*	0.08*	0.09*	0.12*	0.09*	-	1													
8 Education	0.13*	0.20*	0.22*	0.22*	0.05*	-	0.31*	1												
9 Fear of Failure (yes=1)	0.01	-	-	-	-	0.02	-	-	1											
10 Business Rate	-	-	-	-	-	-0.01	-	-	0.05*	1										
11 Population Size (millions)	0.21*	-	-	-	0.03*	-	0.05*	-	0	-	1									
12 Population Growth (%)	-	-	-	-	0.02	-	-	-	-	-	-	1								
13 GDP development stage (2nd quintile)	-	-	-	-	-	0.02*	-	-	-	0.12*	0.09*	0.12*	1							
14 GDP development stage (3rd quintile)	0.06*	-	-	-	-	-	0.02*	-	-	0.03*	0.33*	0.07*	-	1						
15 GDP development stage (4th quintile)	0.06*	0.04*	0.04*	0.14*	-	0.01	0.03*	0.004	0.01	0.21*	0.07*	-	-	-	1					
16 GDP development stage (5th quintile)	-	0.65*	0.64*	0.52*	0.06*	0.11*	0.02	0.16*	-	-	-	-	-	-	-	1				
17 GDP Growth (%)	0.13*	-	-	0.08*	0.003	-	0.06*	-	-0.01	-	0.60*	0.04*	0.16*	0.19*	-	-	1			
18 Number of Procedures	0.06*	-	-	-	-	-	-	-	0.003	-	0.57*	0.49*	0.17*	0.35*	-	-	0.48*	1		
19 Registration Cost	-	-	-	-	0.03*	0.001	-	-	0.002	-	0.07*	0.58*	0.23*	0.12*	-	-	-	0.57*	1	
20 Paid-in Minimum Capital	0.08*	-0.02	-0.01	0.07*	0.01	-	0	-	-	0.03*	0.59*	-	0.13*	0.47*	-	-	0.57*	0.43*	0.13*	1
21 Financial Development	0.09*	0.68*	0.68*	0.69*	0.02*	0.13*	0.04*	0.14*	-	-	-	-	-	-	0.41*	0.56*	-	-	-	-

AIDES = Asian Index of Digital Entrepreneurship Systems, GDP = gross domestic product, Max = maximum, Min = minimum, Std. Dev. = standard deviation, *= Indicates correlation coefficients significant at 5% level or better.

Note: Number of observations: 11,741.

Source: Authors.

Appendix 2 Heterogeneity of Entrepreneurial Businesses

It follows from the heterogeneity of third-person opportunities that new, entrepreneurial firms tend to be a highly heterogeneous group who engage in a broad range of different activities. These activities differ in terms of their substantive content (i.e., what the business does), the location-specificity of the firm's activities and its customer demand, the form of specialisation, and the form of innovation (if any). Combined, these characteristics set up the productivity potential of the new business, i.e., its ability to contribute to economic development.

Firm-level *productivity* captures the efficiency with which it converts inputs (e.g., capital, labour) into value-added (Gal, 2013). Different types of entrepreneurial start-ups tend to exhibit different productivity potential. Disregarding destructive entrepreneurial activity, typically the lowest levels of productivity potential are exhibited by self-employed and small service businesses, such as small shops, street vendors, and similar. Although such businesses provide occupation for the self-employed, the absence of economies of scale hampers the ability of such businesses to make a major contribution to Total Factor Productivity. Instead, the productivity potential of self-employment activity is more likely regulated by the entrepreneur's personal human capital, with more highly educated entrepreneurs exhibiting higher productivity potential, as they are able to draw on their sophisticated human capital to offer knowledge-intensive services (e.g., legal services, financial consultancies, self-employed software specialists).

Low- to medium-technology manufacturing SMEs can exhibit higher productivity potential, provided they are able to scale up their operation. Many low- to medium-technology SMEs operate in supply chains, where they create specialized outputs. They therefore can have an important role to play in, e.g., regional clusters, as facilitators of supply-chain effectiveness and related productivity. This productivity potential will depend on the degree with which these firms are able to co-specialize their interactions with other supply chain firms, thereby enhancing their efficiency.

The two categories offering the highest productivity potential are the two most innovative ones: high-technology new ventures that commercialize new technologies and digital new ventures. High-technology new ventures are entrepreneurial firms who develop applications of high-technology products and services. These can also be referred to as 'technology push' businesses, given their role in commercializing outcomes from RandD. Depending on the scope of the application (e.g., narrow vs broad, with a broad scope of application being typical of generic technologies), the potential impact of high-technology new ventures can be very high. High-technology new ventures cover both those specializing in physical technologies (e.g., biotech, medical tech, chemistry and new materials, and physical science and engineering)

and software applications (e.g., smartphone applications, machine learning algorithms, embedded software).

Finally, digital new ventures deserve a mention as a specific category of new ventures. Digital new ventures leverage resources available through the internet to innovate new ways of creating, delivering, and capturing customer value – i.e., creating business model innovations. A business model defines the activity architecture through which the business creates and delivers value for its customers and captures choices such as: that activities the firm carries out by itself and what activities it outsources to partners; what are the key resources of the business; how customer channels and relationships are organized; what is the value proposition the business delivers to customers; what are the customer groups; how it generates revenue; and what the cost structure of the business is (Amit and Zott, 2012; Zott and Amit, 2010). Over the past decade and a half, business model innovation has become a very important form of entrepreneurial innovation, driven by advances in digital technologies (Autio, Cao, Chumjit, Kaensup, and Temsiripoj, 2019a). This is because digital technologies are communication and coordination technologies, and therefore, able to support even radical re-think of how businesses should organize their value creation and delivery activities. For example, online platforms and marketplaces support new ways of connecting supply and demand. The combinability of digital technologies enables the creation of previously unfeasible combinations, e.g., by enabling the combination of insurance services with health monitoring technologies to support new insurance products. In general, digital technologies enable a much more extensive outsourcing of activities and services even for smaller businesses, enabling these to address a broader range of opportunities that might previously have been inaccessible to them (Nambisan, 2017). Services such as Grab taxi and AirBnB have enabled start-ups to achieve fast growth without having to invest in capital-intensive assets to operate their service. Because digital start-ups are able to challenge established industry incumbents with novel business models, they can potentially act as an important driver of industry and economic restructuring to better fit the digital age, thereby helping make potentially important contributions towards the country's Total Factor Productivity (Autio et al. 2019b).

In Table B1, we highlight differences between types of entrepreneurial activity. As can be seen, new and entrepreneurial businesses vary considerably in terms of their dominant activity, their patterns of innovative activity, the location specificity of their activities, resources, and demand, as well as in terms of their resulting productivity potential and ability to contribute to economic development. As is clear from Table 1, the different categories also differ in terms of their clustering patterns and the types of policy initiatives required for their facilitation.

Table B1 Different Types of Entrepreneurial Businesses and Their Productivity Potential

Type of business	Description of the business	Specialisation and innovation drivers	Location specificity of activities	Location specificity of demand	Productivity potential	Impact of Digitalisation
Local service businesses	Low-technology service providers such as personal services, cafes and restaurants, transport services, construction and maintenance services	Reputation based on service quality or price, location specificity, business premises, personal relationships, branding	Highly localised with local sourcing of resources and supplies	Highly localised	Low	Mobile connectivity enables vendors to connect to suppliers and customers in new ways, boosting revenue.
Low- to medium-technology SMEs	Low- to medium-technology manufacturing businesses operating in supply chain niches or manufacturing specific products (e.g., parts and component suppliers, furniture manufacturers, similar	Mainly through process innovation in the form of specialised manufacturing assets and co-specialised investment in user-supplier interactions; also through product innovation and branding	Mainly localised supply chain relationships	Localised (for supply chain interactions), regional, national, and even international for specific products	Low to medium	Digitally enhanced supply chain interactions help optimise operations, helping boost productivity.
High-technology new ventures	High-technology businesses that commercialise technology-based products	Mainly product innovation by translating advances in basic and applied research and development into new, innovative products	Typically depend on localised spill-over of knowledge from research-intensive activities and local specialised resources such as specialised human capital	Typically national and international, sometimes even global	High	Adding digital elements in products and services can boost value creation. Digitalisation also makes it easier to outsource activities, reducing capital investment.
Software businesses	Software development businesses who code useful functionalities in algorithmic form (e.g., accounting software, smartphone applications)	Product innovation in the form of codification of useful functionalities in software packages	Increasingly tapping non-localised spill-over of knowledge and ideas distributed through digital platforms. In addition, rely on regional specialised resources such as human capital and funding	National, international, and global, especially if software is offered through application software platforms such as Google Play	High	Software products are easily scalable, enabling rapid boosting of sales if the product is successful
Digital new ventures	Businesses that rely on digital technologies and infrastructures for the delivery and coordination of digital and non-digital services (e.g., personal transportation and delivery websites, accommodation service websites, bookkeeping services)	Business model innovation in the form of digitally enhanced, organised, and coordinated services	Tapping into partly localised insights regarding 'what works' in terms of digitally enhanced business model innovation derived from business model experiments. In addition, rely on regional specialised resources such as human capital, funding, new venture accelerators	National, international, and global, depending on the type of service (typically need to connect with localised resources such as cab drivers, physical accommodation providers, similar)	Medium to high, depending on ability to establish platform leadership	Digital ventures are enabled by rapid advances in digital infrastructures, notably in the cloud, which enable digital new ventures to compete with radical business model innovation

Source: Authors.

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