Impact of Government Incentives on Digital Content Creators in Malaysia: An Empirical Study

Andrew Jia-Yi Kam[a]
Universiti Kebangsaan Malaysia

Mohd Jalallul Alam Jasni Zain bin Mohd Isa[b]
Malaysia Digital Economy Corporation

Nazuraida binti Che Yusof[c]
Malaysia Digital Economy Corporation

Abstract: The emergence of the digital creative content industry in Malaysia, highlighted in the *Twelfth Malaysia Plan*, reflects the nation's pursuit of a share in the global digital market. Government initiatives, manifested through grants and incentives, aim to bolster the industry, but their effectiveness remains uncertain. This study explores the impact of these initiatives on digital content creators, utilising firm-level databases from the Malaysia Digital Economy Corporation. Employing parametric tests, the stochastic frontier model, and the panel model, the research reveals that pairing small funds with effective developmental programs yields superior results. Grant recipients exhibit notable growth in job creation – particularly among local skilled workers – heightened research and development (R&D) activity, and increased productivity and profits. Future grant policies should incorporate knowledge sharing from successful recipients and emphasise mentoring, while also supporting industrial training for educators to align curricula with industry expectations.

Keywords: Digital creative content industry, digital economy, Malaysia, policy evaluation, stochastic frontier model
JEL classification: C1, D24, H2, L8, O31

1. Introduction

Digital creative content industries (DCCs) are sectors that focus on value creation through creativity, skills, human capital and the commercialisation of intellectual properties using digital technology. They represent an interplay between human

[a] Institute of Malaysian and International Studies, Universiti Kebangsaan Malaysia, 43600 UKM, Bangi, Malaysia. The author is also Visiting Fellow, Department of Finance, Ming Chuan University, 250 Zhong Shan N. Rd., Sec. 5, Taipei 111, Taiwan. Email: Andrew@ukm.edu.my (Corresponding author)

[b] Malaysia Digital Economy Corporation (MDEC), 2360 Persiaran APEC, 63000 Cyberjaya, Malaysia. The author was previously affiliated with MDEC but is now with the Securities Commission Malaysia. Email: jalallul.alam@seccom.com.my

[c] Malaysia Digital Economy Corporation (MDEC), 2360 Persiaran APEC, 63000 Cyberjaya, Malaysia. Email: nazuraida@mdec.com.my

Article Info: *Received* 16 December 2023; *Revised* 19 April 2025; *Accepted* 26 April 2025
https://doi.org/10.22452/MJES.vol62no1.1

creativity, intellectual property, knowledge and technology.[1] These industries form an essential part of the creative economy, which was valued at USD985 billion in 2023 and is growing rapidly. According to G20 Insights, the creative economy may contribute 10% of global GDP by 2030, while Deloitte projects that the creative sectors could expand by up to 40% by the same year (Bogachev, 2023).

The industry includes activities such as advertising, architecture, arts and crafts, design, fashion, film, video, photography, music, performing arts, publishing, research and development, software, computer games, electronic publishing and TV/radio broadcasting. Beyond generating commercial value, it also serves as an important source of cultural branding and dissemination (e.g., *anime* is associated with Japan, and *manhwa* or *manga* with Korea and Japan). DCCs leverage the growing importance of digital adoption and played a significant role as a source of economic growth during the COVID-19 pandemic.[2]

With e-commerce revenue in ASEAN projected to reach USD80 billion by 2024 (Google, Temasek, Bain, 2020), both opportunities and challenges lie ahead for DCCs. However, fundamental issues – such as the lack of a universally agreed-upon definition for the sector – undermine effective policy development. This has created substantial challenges for government institutions in drafting and evaluating the effectiveness of policy instruments aimed at supporting the DCCs.

In defining the industry, the National Creative Industry Policy of Malaysia categorises the creative industry into three segments: creative multimedia, creative arts and culture, and creative cultural heritage. According to the Department of Statistics Malaysia (DOSM),[3] the industry is still in its developmental stages but shows great potential as a source of economic growth. The creative industry's contribution to GDP saw a modest increase from 1.89% (USD6.5 million) in 2017 to 1.94% (USD7.4 million) in 2019, with nearly 51% of this total contributed by the creative multimedia sector.[4]

Over the years, the animation and digital content industry has demonstrated significant potential in terms of revenue, sales and employment generation. The Malaysia Digital Economy Corporation (MDEC)[5] reported a compound annual growth rate (CAGR) of 6% in revenue, 35% in export sales and 4% in employment from 2013 to 2017. In 2019, the industry generated USD1.8 billion in revenue, USD0.3 billion in export sales and created 10,897 jobs.

This impressive progress, however, is overshadowed by the fact that the market size of Malaysia's digital creative content (DCC) industry is merely one-tenth that of the

---

[1] https://unctad.org/topic/trade-analysis/creative-economy-programme – accessed 11 December 2020.

[2] Studies have shown that 40 million new users went online for the first time in Southeast Asia in 2020, almost doubled the average increase of 25 million yearly in the past four years (Google, Temasek, Bain, 2020).

[3] Data presented during the creative economy 2021 forum "Overview of the Creative Industry of Malaysia and Its Future Outlook".

[4] Which includes: i) Film and television productions, ii) Advertising, iii) Design arts, iv) Animation and digital content (DIKN, https://www.arteri.com.my/learn/policies/dikn/ – accessed 11 December 2020).

[5] MDEC is one of the key agencies implementing government policies with regards to the development of digital economy in Malaysia. https://mdec.my/digital-economy-initiatives/for-the-industry/entrepreneurs/digital-creative-content/ – accessed 11 December 2020.

United States – the world's largest content market (KOCCA, 2018).[6] This suggests that industry players in Malaysia have yet to fully harness the potential of the global digital content market. While numerous government-led initiatives and funding schemes have been introduced to support digital content creators, the impact of these efforts has yet to be thoroughly assessed, especially in light of the country's renewed aspirations to enhance productivity in the national creative industry[7] through policies such as the Digital Content Ecosystem (DICE) and the *Twelfth Malaysian Plan, 2021–2025* (EPU, 2021).

While there are many types of incentives in Malaysia – mainly in the form of pioneer status, investment tax allowances and reinvestment allowances, this study focuses on sector-specific incentives. More specifically, it examines activity-specific incentives (or grants), such as those for R&D and training, in the DCC sector. Incentives or grants are important because they reduce the cost of investment (e.g. capital allowances) and lower the risk (de-risking) of private investments (World Bank, 2017). Activity-based incentives enhance competitiveness when paired with a stable business environment. However, documentation of their effectiveness in Malaysia remains sparse, largely due to data sensitivity.

This study attempts to bridge that gap by empirically evaluating the impact of key policies within the DCC industry. To date, it is the first study to utilise two unpublished firm-level datasets from the Malaysia Digital Economy Corporation (MDEC) – namely the undisclosed *Annual & Quarterly Industry Report* (AQIR) database and the *Digital Content Fund* (DCF) database. It analyses the impact of grants on the performance of creative content companies by comparing firms that received grants with those that did not.

This study is significant as it supports data-driven policy evaluation in the policy-making process. It aligns with the country's main economic framework – the *Twelfth Malaysia Plan, 2021–2025* – which emphasises evidence-based policy (EBP) as a core strategy for driving productivity growth. A caveat, however, is that this study does not aim to isolate the effectiveness of specific grants (e.g., DC3, MAC3 Co-Production, CREED funds), but rather to examine broader aspects and challenges of policies that may contribute to the industry's growth objectives.

Section 2 provides a literature review. Section 3 offers an overview of policy initiatives and presents industry profiles based on three unpublished micro- or firm-level databases from MDEC: an annual survey (2018–2020), the AQIR database, and the DCF database. Section 4 examines the impact of grants on the performance of recipient and non-recipient firms. It also models the effect of grants on firm productivity and profits using the stochastic frontier and panel model. Section 5 concludes.

2. Literature Review

Based on neoclassical assessment methods, the efficacy of state support can be evaluated through various aspects such as its influence on firm inputs, outputs and other forms of support (*additionality*) (Hall & Maffioli, 2008). This additionality component is often

[6] Refer to KOCCA (2018), 2017 Survey of Overseas Content Market, Table 2-2, p. 23.

[7] https://www.astroawani.com/berita-malaysia/national-creative-industry-policy-must-be-improved-saifuddin-244481 – accessed 11 December 2020.

interpreted as grants, incentives or other support provided *in addition* to neoclassical inputs (capital and labour), and is commonly examined through comparative studies between grant recipients and non-recipients. Literature on the impact of grants generally assesses either (i) the types of grants (such as research or development grants) or (ii) development activities such as grants given across different segments of the value chain (Clausen, 2009; Hottenrott et al., 2017; OECD, 2002). McKenzie (2017), using a theoretical model, illustrated a general increase in the optimal value of output for firms with additional grant funding. This, however, only applies depending on the Lagrange multiplier used, meaning, the theoretical model attributes the positive impact of grant money to the size of the funds – which is subsequently associated with firm size.

Government incentives play a crucial role in shaping firm performance by influencing investment and operational decisions. These incentives may take various forms, including tax breaks, subsidies, grants and loans. When properly structured and implemented, they can enhance business performance, boost productivity and competitiveness, and ultimately drive economic growth. However, evaluating the impact of grants on firm performance is closely tied to the input and output indicators selected. For instance, some studies have identified a significant positive impact of grants on employment (Colombo et al., 2013; Criscuolo et al., 2019). Bronzini and Piselli (2016) found evidence that government grants stimulate innovation, which subsequently contributes to economic growth. These effects tend to be more significant for smaller firms than for larger ones. Consequently, the prevailing approach in the literature is to evaluate grants using output-oriented indicators (output additionality) such as value-added, sales, profits and employment – outcomes directly influenced by input upgrading (input additionality), such as capital stock or R&D expenditures (Howell, 2017; Michalek et al., 2015; Srhoj et al., 2019).

Grants also allow for the reallocation of resources toward higher-skilled workers, thereby enhancing the technical quality and value of output. However, the impact on profits remains mixed (McKenzie, 2017; Michalek et al., 2015; Srhoj et al., 2021). This ambiguity is linked to the relationship between grants and profitability, whereby more profitable firms tend to receive smaller grants or are less likely to qualify for start-up grants. While some firms can use grants to boost profits, others – particularly less performant firms – may not be able to translate grant support into profits in the short term.

Some grants may also have a negligible effect on firm performance when R&D expenditure is used as the benchmark of success. Hottenrott et al. (2017), for instance, found that business development funds had limited impact on R&D expenditures. Therefore, findings on the impact of grants are often ambiguous or conditional upon the performance metrics employed. Criscoulo et al. (2019) also showed that the effect of grants on productivity is uncertain as there appeared to be no additional effect on productivity after controlling for investment. Furthermore, since less productive firms tend to receive more subsidies, the program may inadvertently lower measured aggregate productivity by increasing the employment share of low-productivity firms.

The effectiveness of incentives and grants has critical implications for the evidence-based policy (EBP) approach. Understanding which instruments and initiatives are effective enables stronger program evaluation and monitoring systems. Although the EBP approach is not new, it has gained renewed attention as one of the key strategies in the *Twelfth Malaysian Plan* for driving structural reform and sustaining productivity and economic growth. Davies (2012) argued that EBP helps policymakers make informed decisions about programs and projects by integrating the best available research evidence into policy development and implementation. While policy processes are rarely linear or cyclical, they can be disaggregated into different stages, where the EBP approach can be applied to strengthen decision-making.

Globally, the digital creative economy has experienced rapid expansion, particularly in areas such as streaming and data monetisation. To capitalise on this potential, developing countries support creative and digital entrepreneurship through robust legal frameworks, financial support and accessible business services (Nurse, 2021). Research on the animation sectors in the UK and China underscores how government policies – through subsidies, regulation, and protection – can shape innovation systems in creative industries at both regional and national levels (Liu, 2021). In China, subsidies and tax incentives foster innovation in digital creative firms, with leadership characteristics acting as a moderating factor (Zhou et al., 2024).

South Korea has introduced various policies to support its digital creative content industry, with mixed results. While subsidies have positively influenced market development perceptions, industry professionals express low overall satisfaction with these policies. The Korea Creative Content Agency plays a pivotal role in advancing creative and cultural content, focusing on sectors such as gaming, animation, webtoons and popular music (Yecies & Shim, 2018). The rapid development of South Korea's information and communication technology (ICT) sector, fueled by sustained R&D investment and unique national strategies, has established a strong foundation for its digital content industry. This industry has thrived on Korea's advanced ICT infrastructure, including widespread high-speed internet, and is anticipated to evolve from network-based to content-based services (Choi & Oh, 2009).

In Japan, the government has prioritised the creative industries as part of its strategy to revitalise the economy and enhance soft power. The 'Cool Japan' initiative supports the global promotion of Japanese media content and creativity-driven exports (Pokarier & Tamiya, 2007). However, challenges persist, including weak international marketing, underdeveloped distribution networks, and resistance to digital adoption. Addressing these issues requires targeted government policies, as evidenced by successful reforms in countries such as Taiwan (Tsai et al., 2008). Malaysia has also leveraged grants and incentives to position itself as a hub for creative content technologies and digital economy growth (AuYong, 2018). However, research on the impact of grants[8] and incentives on the DCC sector remains largely undocumented (Interview with MDEC, 2020).

---

[8] A caveat is that, the term 'grants' here is defined by measurable variables such as incentives, training programs, and grants. While each of the above have individual objectives, the differences are marginal. This will not distort the objective of the study as most policy actions include incentives, training programs and grants. Also, the abovementioned variables were verified as a credible metrics through interviews conducted with members from MDEC. For brevity, the term 'grants' will be used generically throughout the study. The term grants here also include training or incubation programs that have been embedded within MDEC initiatives. Data available on request from the authors.

3. Policy Overview: Government Initiatives Driving the Industry

In Malaysia, policies addressing the development of the Digital Creative Content (DCC) industry have been introduced sporadically. To date, there is no comprehensive document that clearly outlines specific strategies or developmental pathways for the digital creative sector. One of the earliest official documents to highlight digital media and multimedia content is the National Creative Industry Policy (NCIP) (Dasar Industri Kreatif Negara), launched in 2009. This seminal policy aimed to position the creative industry as a key driver in transforming Malaysia into a high-income nation. The NCIP proposed a range of initiatives to boost the competitiveness of the creative sector. These included investments in physical infrastructure, implementation of training and accreditation programs, and promotion of local cultural symbolism and national identity at the global level. The government also supported the industry through grant allocations and by facilitating financing via local banks.

Another important DCC policy development strategy was documented in the Malaysian government's *Economic Transformation Plan* as early as 2010. Three key strategies were introduced namely creative content development, local hosting of content and ecosystem enhancement. Among the key action plans was the digitalisation of creative content for commercial purposes. Both the NCIP and ETP laid a general foundation for creative industry development. However, it was not until 2019 that the term 'digital content' was formally defined and brought to the forefront under the proposed (though still incomplete) Digital Content Ecosystem (DICE) policy (Interview with MDEC, 2020). While currently undergoing amendments, the DICE policy retains a primary focus on four strategic areas: talent development, industry growth, intellectual property (IP) commercialisation and regional market expansion (Interview with MDEC, 2020). This policy signalled a more targeted approach to shaping a digital content ecosystem in Malaysia.

Although the then Ministry of Communications and Multimedia (*now*, under *Ministry of Digital*) is the main custodian of most of the creative content policies, they work closely together with the Malaysia Digital Economy Corporation (MDEC) in creating a digital content ecosystem in Malaysia. Over the years, MDEC has introduced a series of flagship programs, including training initiatives and incubation schemes to nurture industry capabilities. In support of these initiatives, the Digital Content Funds have been made available to finance content development, production, co-production, export acceleration and IP commercialisation. The grants and their corresponding policy objectives are outlined in Table 1.

3.1 Profile of the Digital Content Funds and Firm Performances

The objective of this section is to identify the characteristics of the industry based on two unpublished firm-level databases provided by MDEC. The Digital Content Fund database contains information on the types of grants obtained by the companies, along with the technology focus of each company. The database includes only five documented grants,[9] namely BCI2, MAC3, MAC3 Co-Production, DC3 and DCF (which

[9] For brevity, the term 'grants' will be used generically throughout the study. The term grants here also include training or incubation programs that have been embedded within MDEC initiatives. Data available on request from the authors.

Table 1. Selected Malaysia Digital Economy Corporation (MDEC) grants for the development of the digital content industry up to 2020*

Key initiatives	Policy objectives / Agenda setting
DC3 (formerly known as IPCC)	A platform for local talents to hone their creativity and ability to develop new content ideas. Its main purpose is to help accelerate the development and commercialisation of these concepts and transform them into world-class digital content. It is a grant based on a competition in conceptualising new ideas for content.
Development, production and co-production grant	*Development grant*: Focuses on the development stage of the project, the stage where it involves idea generation, production design, market research and marketing analysis. The development stage is defined as the planning phase of the project. *Production grant*: Focuses on the production stage of the project which involves the activity of creating, assembling, aggregating and generally producing or generating content. *Co-production grant*: Financial assistance to a project within eligible project categories to be co-produced by a Malaysian company and one or more foreign companies, for example, • *Bumiputera Creative Industry Initiative* (*BCI2*) – Conditional grants to support the development, production, enhancement and commercialisation of original I.P. by Bumiputera content creators. The BCI2 fund is designed to provide qualified Bumiputera content companies with the necessary financial support which will accelerate the growth of the company. • *Malaysia Creative Content Center* (*MAC3*) *Fund* – Conditional grants to support concept development, production and co-production projects. Financial support is provided to qualified projects that are either already in the production stage or at the development stage. Note that the MAC3 fund is not for new players or new IP development purposes. • *MAC3 Co-production* – The applicant has entered into a written contract OR a committed arrangement with a foreign co-production partner(s) for the co-production of the project.
Creative Industry Export Acceleration and Enterprise Development (CREED)	An end-to-end fund to address long-term industry growth and sustainability. CREED is designed to support established creative content companies with a history of successful IP development and commercialisation. The applicant has commercialised their previous IP(s) locally or globally.
IP marketing & licensing grants	Financial assistance is provided to IP creators with the market-ready product(s). This includes IP extension, IP registration, development of style guide and other activities related to marketing, promotion, localisation, commercialisation, licencing or distribution.

Note: * There are also grants by other agencies that also support and build the DCC business ecosystem, i.e. Film in Malaysia Incentive (FIMI), Dana Kandungan Digital, etc. While the study acknowledges the contribution of these funds, the focus of the study will only be on the ones implemented by the Malaysia Digital Economy Corporation (MDEC) due to the availability of data. Additionally, these funds were available at the time of the research, but their names/availability may have changed over the years.

Source: https://mdec.my/digital-economy-initiatives/for-the-industry/entrepreneurs/digital-creative-content/

consists of Development, Production, Co-Production, CREED, IP Licensing & Marketing). The more extensive *Annual Quarterly Industry Reporting* database consists of firm-level characteristics of DCC players from 2009 to 2019. It contains information on firm size, capital, operational expenditure and employment. Both databases were then combined, and this section presents the findings.

Over the years, the total amount of grants disbursed by MDEC has fluctuated. It peaked at around USD20 million in 2010, but subsequent years have seen a decline in the total amount (Figure 1). This decline may have been driven by the sudden drop in the disbursement of the MAC3 Co-Production Grant (Figure 2). Further interviews with stakeholders and the MDEC team suggest that the terms and conditions of the fund were not well received. Since co-production funds involve joint production with foreign partners, the rigid terms and conditions led to many unsuccessful partnerships. However, the terms may have improved, as Figure 2 shows an increase in the disbursement of the grant since 2011.

Animation companies have received the highest number and value of grants (Table 2). This is expected, as the composition of DCC players in Malaysia is predominantly focused on animation, followed by the digital game sector and digital films with virtual effects (VFX). Firms in digital films with VFX have received more BCI2 and MAC3 grants compared to others.

4. Empirical Analysis

4.1 Differences between Grant and Non-Grant Recipients

To empirically analyse the differences in firm performance, another unpublished database (Digital Content Fund) is utilised.[10] In this database, the number of establishments that have received grants from 2009 to 2019 amounts to 547. This pales in comparison to the 2,795 non-grant takers in the database during the same period. Therefore, the discussions cannot merely rely on aggregated nominal values.

Table 3 highlights the impact of grants on employment generation and skills development in the DCC industry from 2009 to 2019. Grant-supported companies experienced significantly higher growth in total jobs (19%) compared to non-grant companies (4%), as well as greater labour productivity growth (42% vs. 26%). Additionally, grant recipients allocated 19% of total sales to R&D, far surpassing the 1% reported by non-grant companies, underscoring the role of grants in fostering innovation and productivity.

Workforce composition reveals a similar share of local skilled workers in both groups (56% for grant-supported and 55% for non-grant companies), while the share

[10] The database comprises three components: i) *Financial Performance*, which includes data on sales, export sales, R&D expenditure, total profit and loss, total capital and operational expenditure, and salaries; ii) *Human Resources*, which requires companies to provide information on the total number of permanent and contract staff, the composition of foreign and local workers, categorisation into knowledge and non-knowledge workers, and the total number of jobs; and iii) *Company Profile*, which includes the company's name and other relevant details. The *Annual & Quarterly Industry Report* (AQIR) is then matched with the information in this database.

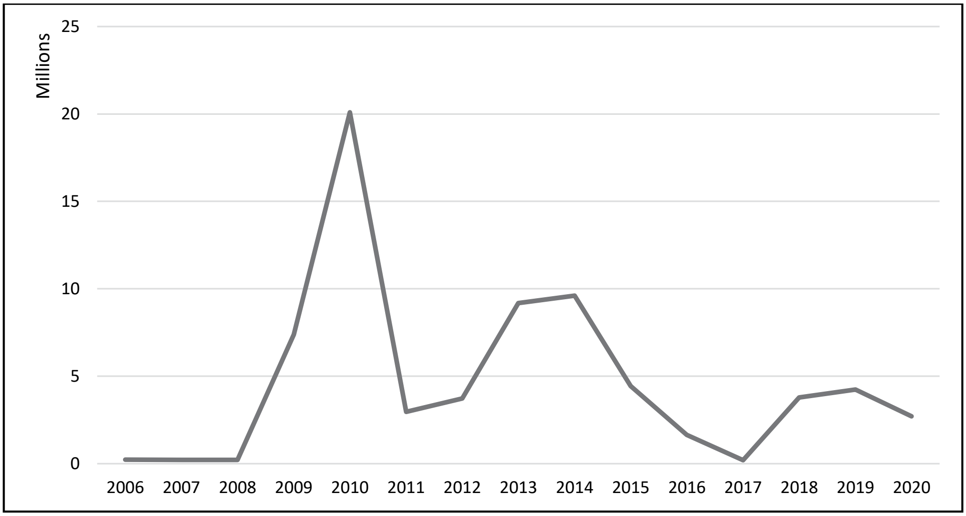

Figure 1. Total grants disbursed, 2006–2020 (USD million)
Note: Amount converted using the exchange RM4 = 1USD.
Source: Digital Content Fund, Malaysia Digital Economy Corporation (MDEC) (unpublished).

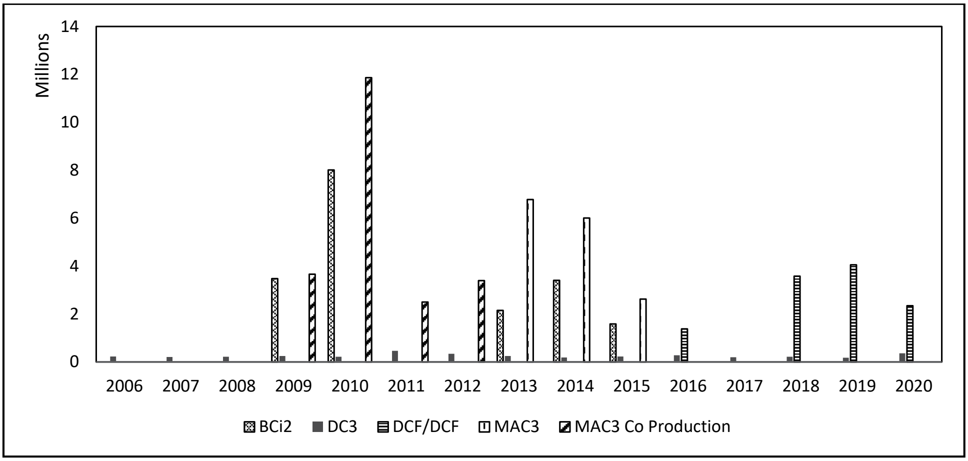

Figure 2. Value of grants given, by type (USD million)
Source: Digital Content Fund, MDEC (unpublished).

Table 2. Selected top sectors receiving Malaysia Digital Economy Corporation (MDEC) digital content grants, 2006–2020

Grants / Technology	Total number	Total grants (USD million)
DC3	357	3.8
Animation	79	1.0
Casual games	70	0.9
BCi2	67	18.7
Animation	43	13.2
Digital film with VFX	16	3.9
Digital games	4	0.9
DCF	31	9.0
Animation	16	6.0
Digital games	14	2.9
Beyond entertainment – Digital comic	1	0.1
DCG	17	2.4
Animation	14	2.0
Digital games	3	0.4
MAC3	71	15.4
Animation	29	7.5
Digital film with VFX	26	3.5
Digital games	8	2.6
MAC3 co-production	20	21.4
Animation	17	18.1
Digital games	2	2.1
Digital film with VFX	1	1.3
Grand total	563	70.6

Source: Author’s calculation from Digital Content Fund, MDEC (unpublished).

Table 3. Employment generation and skills level of the DCC industry

No.	Average growth, 2009–2019 (%)	Grant	Non-grant
1.	Average growth in total jobs	19	4
2.	Average growth in labour productivity	42	26
3.	Average share of R&D in total sales (%)	19	1
4.	Average share of local skilled workers to total	56	55
5.	Average share of foreign skilled workers to total	8	4

Source: Calculated by author from *Annual & Quarterly Industry Report* (AQIR) and Digital Content Fund database (unpublished).

of foreign skilled workers was higher among grant recipients (8% vs. 4%). This suggests that grants enable companies to attract diverse talent, which can contribute to innovation and knowledge transfer. Overall, the data demonstrates that grants significantly enhance job creation, productivity and R&D investments in the DCC industry, reinforcing their importance in driving industry growth and competitiveness.

4.2 Parametric Method

The differences between grant and non-grant-receiving companies are further analysed using two parametric tests: the independent sample t-test and the paired sample t-test. A total of 20 variables were tested, ranging from growth and share in total sales, local and foreign sales, total jobs, permanent and contractual jobs, local and foreign jobs, R&D expenditure and profit/loss. For brevity, only the statistically significant variables are displayed here. The full results of the test are shown in Appendix 1.[11] A caveat to this section is that the analysis does not imply causality but is intended to identify key variables that may differ based on whether a firm is a grant recipient or not. This univariate comparison highlights potential areas of impact; however, it does not control for other factors that could influence these variables. Therefore, the results should be interpreted as descriptive insights rather than evidence of causal relationships.

1) The *Independent Sample T-test* examines the differences between grant recipients and non-recipients. The test uses the entire population of the database:

$$t = \frac{M_1 - M_2}{\sqrt{\frac{SD_1^2}{n_1} + \frac{SD_2^2}{n_2}}} \tag{1}$$

with M as the sample means, SD as the standard deviation, and n as the total number of firms. Notations for 1 and 2 are grant recipients and non-recipients.

Table 4 presents only the statistically significant variables from the test. The results indicate that grant recipients exhibit higher average job growth – particularly among local skilled workers. The findings also confirm that grant recipients differ significantly from non-recipients in their use of permanent and contract skilled workers. The mean differences suggest that grant recipients employ more permanent and contract skilled workers in their operations. Notably, only job-related indicators show consistent statistical significance, implying that MDEC grants have a strong impact on job creation within the industry.

2) *Paired-samples t-test* follows a company and tests whether there are improvements ‘before taking grant’ and ‘after taking grant’. This method uses only samples of firms that have taken the grant:

$$t = \frac{X_{diff} - 0}{S_x} \quad 2)$$

[11] Due to the study’s focus on identifying key variables with significant differences between grant-receiving and non-grant-receiving companies, only statistically significant results are presented in the main text for clarity and relevance. Full results for all variables, including non-significant findings, are available in the supplementary materials (Appendix 1) to ensure transparency and comprehensive reporting.

Table 4. Statistical differences between grant recipients and non-recipients (independent sample t-tests)

Independent samples test

		Levene's test for equality of variances[12]		t-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference	
									Lower	Upper
Total job growth	EVA	29.632	.000	2.893	3337	.004	12.42608	4.29566	4.00369	20.84848
	EVNA			2.068	662.158	.039	12.42608	6.00744	.63016	24.22201
Local skilled worker growth	EVA	28.351	.000	2.192	3337	.028	9.35864	4.26977	.98701	17.73026
	EVNA			1.664	682.549	.097	9.35864	5.62333	-1.68247	20.39974
Share in skilled worker	EVA	49.994	.000	5.294	3337	.000	7.96283	1.50419	5.01361	10.91205
	EVNA			4.839	772.590	.000	7.96283	1.64551	4.73262	11.19304
Share in foreign skilled worker	EVA	14.085	.000	-1.436	3337	.151	-.01367	.00952	-.03234	.00500
	EVNA			-1.800	1132.038	.072	-.01367	.00760	-.02858	.00123
Share in permanent skilled worker	EVA	32.082	.000	2.840	3337	.005	.05521	.01944	.01710	.09333
	EVNA			2.984	883.502	.003	.05521	.01850	.01889	.09153
Share in contractual skilled worker	EVA	136.033	.000	9.282	3337	.000	.09854	.01062	.07772	.11935
	EVNA			7.857	729.356	.000	.09854	.01254	.07392	.12316

Note: EVA – Equality of variance assumed, EVNA – Equality of non variance assumed.
Source: Calculated by author from *Annual & Quarterly Industry Report* (AQIR) and Digital Content Fund database (unpublished).

[12] Levene's test is conducted to assess whether the assumption of homogeneity of variances is met before performing a t-test. This test ensures the validity of subsequent analyses by identifying variance inequality, which can be particularly problematic in the presence of substantially unequal sample sizes. In this case, the assumption of equal variances holds, as indicated by the results of Levene's test. However, given the significant disparity in sample sizes between grant-receiving and non-grant companies, the results will be interpreted with caution to account for any potential biases arising from the imbalance.

with X_{diff} presenting the difference in mean differences before and after a firm received grants, S_x is the unbiased standard deviation.

Table 5 suggests an increase in R&D activities following the receipt of grants. There is also a higher employment of local skilled workers in these companies compared to the period before receiving the grants. Additionally, the test indicates an improvement in profitability among grant-recipient companies, implying a possible reduction in input costs. These outcomes may be interrelated, as grants could have contributed to higher profitability by enhancing productivity through the employment of skilled workers and improving efficiency via R&D activities.

Table 5. Statistical differences between before and after receiving grants (paired sample t-tests)

Paired samples test										
Mean (before grant) − Mean (after grant) = 0		Paired differences					t	df	Sig. (2-tailed)
		Mean	Std. deviation	Std. error mean	95% confidence interval of the difference				
					Lower	Upper			
Pair 1	Share of R&D expenditure in total sales	-80.5	183.2	31.0	-143.4	-17.5	-2.6	34	.014
Pair 2	Share of local skilled worker	-22.9	44.3	7.4	-37.9	-7.9	-3.1	35	.004
Pair 3	Growth in profit	-434.1	1114.0	227.4	-904.4	36.3	-1.9	23	.069

Source: Calculated by author from *Annual & Quarterly Industry Report* (AQIR) and Digital Content Fund database (unpublished).

At this juncture, the study has identified several key characteristics of grant-recipient companies: stronger job creation capacity, better sales performance, greater utilisation of R&D and improved profitability.[13] However, there are still areas that require attention. Notably, the results have yet to demonstrate any improvement in export sales following the receipt of grants. While the findings suggest that the domestic market is maturing and there is a growing focus on local distributors, the development of a robust digital ecosystem ultimately requires expansion into international markets to position Malaysia as a leading digital content hub in the region.

Despite this limitation, the overall outlook for the Malaysian DCC industry remains positive. Core fundamental indicators such as job creation, profitability, and steady growth are showing consistent improvement.

At this stage, the findings offer only a snapshot of firm performance. The current analysis lacks key performance indicators such as sales growth and productivity, which

[13] A caveat is that, this does not mean non-grant takers are not profitable in their businesses, the result merely suggests that grant-recipients achieved better results.

were not captured by the t-test due to its focus on mean differences and its inability to account for more complex relationships or variability among firms. Therefore, Section 4.1 undertakes a deeper investigation into the impact of grants on these indicators, incorporating additional variables and potential confounders. The causal relationship between productivity and grants will be examined next.

4.3 Stochastic Frontier Model: Impact of Grants on Productivity and Technical Efficiency

To identify technical efficiency (TE), this study uses another strand of productivity measurement approach called the stochastic frontier analysis (SFA). It is an extension of the total factor productivity (TFP) method and fits various conditions of the study. The concept of 'frontier' analysis hinges on the idea of a maximal or 'best practice' approach to production. It is an estimation of a production frontier that is benchmarked against the best-performing firms. There are conditional requirements for using the SFA approach. One of which is that it is more suitable for firm-level studies. This is because benchmarking an aggregated unit, e.g. country or industry does not make sense as countries/industries do not function as independent units that increase technical efficiency. Additionally, firms should belong to a homogeneous industry to ensure that efficiency benchmarks are conducted among comparable firms. It would be inaccurate, for example, to benchmark a petrochemical firm against one in the digital content industry, as they operate in entirely different sectors. The same applies to country- or industry-level studies, unless they meet certain homogeneity criteria. Given these conditions, the use of stochastic frontier analysis (SFA) is appropriate for this study.

Based on Aigner et al. (1977) and Meeusen and van Den Broeck (1977), the formulation of the stochastic frontier model in terms of general production function can be specified as:

$$Y_i = f\left(X_{i,}\beta\right) + \upsilon_i - u_i = f\left(X_{i,}\beta\right) + \varepsilon_i \tag{3}$$

where Y_i is a scalar output of the ith digital creative content companies (DCC), X_i is the vector that collects direct inputs and β is the vector of parameters to be estimated. ε_i is a composed error term where υ_i is a two-sided 'noise' component assumed to be independently and identically distributed (iid), symmetric and distributed independently from u_i. It captures the effects of random shocks beyond the control of DCC (i.e., measurement errors as well as other noise). u_i is a non-negative ($u_i \geq 0$) *technical inefficiency component* of the error term that captures the factors that are under the control of the producer (i.e. determinants of inefficacy to be defined in the inefficiency model). u_i is assumed to be independently and identically distributed as normal-half-normal distribution (Aigner et al. 1977). While there are other possible specifications of the distributional assumptions on u_i (i.e. truncated-normal distribution) suggested by Greene (1980) and Lee (1983) which are still being used in empirical work. Jondrow et al. (1982), Battese and Coelli (1992, 1995), suggested that the half-normal model is the most common formulation. Other variants such as the truncated-normal model with heterogeneity in the mean allow for great flexibility in the modelling tools.

The inefficiency component (u_i) of the error term is the log difference between the maximum and the actual output (i.e. $u_i = lnY_i^* - Y_i$), therefore u_i x 100% is the percentage by which actual output can be increased using the same inputs if production is fully efficient (Kumbhakar & Wang, 2015). In other words, it is the percentage of output that is lost due to technical inefficiency. The estimated value of u_i is referred to as the output-oriented (technical) inefficiency, with a value close to 0 implying full efficiency. Rearranging (1), we can derive the following equation for technical efficiency:

$$TE_i = exp\left(-u_i\right) = \frac{Y_i}{Y_i^*} = \frac{Y_i}{f\left(X_i,\beta\right)exp\left\{\upsilon_i\right\}} \tag{4}$$

which defines the digital content firms' technical efficiency as the ratio of observed output (Y_i) to the frontier output (Y_i^*) which represents the maximum feasible output under the current technology. This maximum output is influenced by the stochastic components of the environment, represented by υ_i, capturing random variations that affect the firm's performance. Because $u_i \geq 0$, the ratio is bounded between 0 and 1, therefore a DCC achieves maximum efficiency if, and only if, $TE_i = 1$. Otherwise $TE_i \leq 1$ is a shortfall of observed output from the maximum feasible output in an environment characterised by υ_i that is stochastic and varies across DCC.

The model uses panel stochastic frontier estimation on 57 companies from 2009 to 2019.[14] The true fixed-effect model is used, and the inefficiency term is assumed to follow a truncated normal distribution. The stochastic frontier is estimated using the maximum likelihood estimator. It is important to note that in the context of stochastic frontier analysis (SFA), the dependent variable represents the output of the production process, which is decomposed into two components: a deterministic frontier component, modelling the maximum achievable output given inputs and technology, and an inefficiency component, quantifying the shortfall from this maximum due to technical inefficiency. Additional exogenous variables are examined to identify the determinants of (in)efficiency. This is where grants are introduced to determine whether they impact firm productivity. In addition to grants, other control variables may also influence firm productivity and efficiency:[15]

Export sales − Exporters must compete at international standards, which requires digital content companies (DCCs) to be efficient in resource use and familiar with best practices. Through the export-by-learning process (Kam, 2016), exporters gain broader knowledge of international product quality standards and management practices. With increasing competition in international markets, exporters must also enhance their efficiency, stay updated on the technological frontier of their products, and continuously upgrade their production technology.

Labour productivity − Increased labour productivity, whether through the addition of machines or not, leads to greater efficiency. It also serves as a proxy for a workforce

[14] The initial dataset of 3,342 companies was reduced to 57 firms with 240 observations after applying panel stochastic frontier analysis (SFA). This reduction occurred due to sfpanel requirements, which exclude firms with incomplete data, insufficient continuous panel observations over 2009–2019, and invalid values for variables requiring logarithmic transformations. The final sample ensures compliance with model specifications and robust analysis.

[15] While there are many other determinants of inefficiency (based on extensive literature), the study is only able to utilise available variables from the *Annual & Quarterly Industry Report* (AQIR) and DCF database. Additional variables will be left for further research.

that is becoming more diverse, skilled and better trained due to upskilling development programs.

Increase in R&D as a share of total sales – Increased market or product research could improve sales. However, a higher share of R&D relative to sales may indicate more resources being allocated to R&D instead of sales activities, such as marketing. As a result, the trade-off effect suggests that the impact of R&D on sales may be ambiguous and could potentially not lead to improved sales efficiency.

The full description of the variables are given in Table 6. The correlation table in Appendix 2 also demonstrates that there are no significant multicollinearity issues among the variables.

Table 6. Variable descriptions

Variable	Description
Stochastic frontier model (identifying the impact of overall grants on efficiency and productivity)	
1. Real sales (dependent variable)	Proxy for output of firms. Since the total value of sales = price x output, output = (value of sales divided by price) or real sales value. The price deflator is taken from the Services Producer Price Index by Group (MSIC) 2008, Malaysia, under the Information and Communication section.
2. Total jobs	Total permanent and contractual jobs.
3. Capital expenditure	Self-explanatory, in RM.
4. Grants	Dummy variable that indicates whether a company has taken any MDEC grants (1 = grant recipients, 0 = non-recipient).
5. Growth in export sales	Annual growth in export sales, %.
6. R&D in total sales	R&D expenditure per exports, in RM.
7. Labour productivity	Total real sales per total of persons engaged.
Panel data estimation (identifying the impact of individual grants on the firm's profit)	
8. Profit growth (dependent variable)	Self-explanatory, in RM. Only values of profit > 0 are considered. This is to prevent values in negative profit (meaning loss) be taken into the growth calculation.
9. Export share	Share of export sales in total sales.
6. R&D expenditure	R&D expenditure (not tied to sales), RM.
7. Labour productivity	Same as above.
8. Grants: BCI2, DC3, DCF, MAC3, MAC3 Co-Production	The average value of grants as a share of total sales of the year. For example, Company X received a Y amount of the BCI2 grant in 2009, with the impact potentially lasting until 2019. Therefore, the average benefit of the grant is calculated as Y divided by 10 years. To introduce variation in the grant's impact, this average benefit is then divided by the sales value for each year, serving as a proxy for the grant's contribution to the sales value in that particular year.
9. Foreign skilled worker (for robustness test)	As a proxy for foreign knowledge spillovers as well. Identify whether there are knowledge spillovers from the utilisation of foreign talent as well as a variable to check the robustness of the panel model.

Source: All variables are obtained from the *Annual & Quarterly Industry Report* (AQIR) and Digital Content Fund (DCF) database (unpublished) unless specified.

An important consideration when estimating the model is identifying the forms of technical efficiency (TE). There are two key types of TE: input-oriented and output-oriented. The input-oriented approach focuses on achieving efficiency by reducing or altering inputs. In contrast, the output-oriented approach examines how efficiency can be improved without changing inputs, by holding inputs constant and increasing output. For the purposes of this study, output-oriented efficiency is therefore considered in the model.

Table 7 shows that technical inefficiency accounts for 66% of the variation in output, justifying the use of the SF model. The frontier model is determined by two statistically significant variables: capital expenditure and total jobs. The year indicator controls for yearly noise in the fixed effects. The negative coefficients in the 'inefficiency model' indicate that grants help reduce inefficiency (meaning, increase efficiency)

Table 7. Empirical output SFA model

	Log real sales
Frontier	
Log total jobs	0.534***
	(9.61)
Log capital expenditure	0.171***
	(8.21)
Year	0.00302
	(0.26)
Inefficiency model	
Grants	-0.235*
	(-2.30)
Growth in export sales	-0.0000148
	(-0.33)
Log R&D in sales	0.274***
	(8.59)
Log labour productivity	-0.278***
	(-27.14)
_cons	3.588
Usigma	
_cons	-2.589***
	(-14.09)
Vsigma	
_cons	-3.252
N	240
Variance	
Variance of TE	0.075
Variance of the unknown term	0.039
Total variance	0.114
TE share	66.0 %

Note: 57 alpha dummies are not reported here. Levels of significance * p<0.05, ** p<0.01, ***p<0.001.

within a company. In the context of SFA, this means that firms receiving grants are more likely to perform closer to the frontier or the industry's 'best practice' production function. Essentially, these firms use capital and labour efficiently to approach the maximum possible sales potential. Similar findings can be observed in other controlled variables, such as labour productivity.

However, an increase in R&D expenditure did not seem to improve efficiency. This could be due to the trade-off effect, as previously explained. Alternatively, R&D may enhance the quality of intellectual property (IP), but the quality of IP may not be directly linked to sales efficiency. Moreover, growth in export sales did not increase technical efficiency, likely because: a) grant recipients are more successful as original IP creators and can sell locally, and b) the evolving local distribution market is more accepting of higher-quality, higher-priced products generated in the domestic market and influenced by related market forces.

Extracting the technical efficiency (TE) values from the model, Table 8 identifies the efficiency range of the industry and its grant recipients. The table shows that players in the animation industry vary in terms of productivity. Animation has the best performers but also the worst (furthest away from the frontier production line). In general, the best DCC performers have efficiency above 50%. However, the mean values also indicate that the performance of companies in the DCC is very much skewed, meaning there is a vast difference between the best performer and the majority of other players. Take the Animation sector, the best performer has an efficiency level of 0.92 but on average there are many performing well below 50% of the frontier production line. Apart from the Digital Interactive Comic sector, other sectors have an average efficiency below 50%. When singled out by grant recipients, DC3 recipients have higher technical efficiency compared to other grant recipients. One reason may be due to the characteristics of the DC3 grant. DC3 is a competition/challenge and the winner of the grant is supposed

Table 8. Technical efficiency range by industry and grants

	Min	Max	Mean	Std. dev.
By industry (entire population)				
Animation	0.05	0.92	0.29	0.16
Digital interactive comic	0.51	0.78	0.61	0.09
Digital film with VFX	0.20	0.69	0.43	0.14
Animation – short	0.38	0.63	0.46	0.08
Digital games	0.10	0.61	0.29	0.16
Mobile games	0.28	0.53	0.40	0.08
By grants (only grant recipients)				
BCI2	0.44	0.61	0.52	0.07
DC3	0.32	0.99	0.58	0.18
DCF	0.44	0.54	0.51	0.06
MAC3	0.36	0.65	0.48	0.08
MAC3 Co-Production	0.44	0.54	0.50	0.05

Source: Calculated by author from the *Annual & Quarterly Industry Report* (AQIR) and Digital Content Fund database (unpublished).

to be more productive and efficient than other candidates. On average, almost all grant recipients are near or above 50% in their technical efficiency levels, implying the recipients are operating closer to the frontier production line.

4.4 Impact of Grants on Profit – A Panel Model

One question remains: Do the grants contribute to the profitability of the companies? The causal relationship will be analysed in this section. This section uses a panel of DCC firms over time. Two standard panel estimation methods are considered: Fixed-effect (FE) and Random-effect (RE) models. The standard pooled estimator assumes no unobserved heterogeneity across time (years) and space (DCC firms). To relax this assumption, either the Fixed-effect (FE) or Random-effect (RE) estimation method is used.[16]

In the fixed effect model:

$$Y_{it} = \beta_i X_{it} + \alpha_{it} + u_{it} \tag{5}$$

where, α_{it} (i = 1……n) is the unknown intercept for each digital content company (n company-specific intercepts).

Y_{it} is dependent variable where i = companies and t = time.

X_{it} represents the independent variables in Table 6 with β_i as its coefficients.

u_{it} represents the error term.

In the fixed-effects model, the α_{it} are allowed to be correlated with the regressors, X_{it}. Note, that $u_{it} = \alpha_{it} + \varepsilon_{it}$.

4.5 Random Effect Model

$$Y_{it} = \beta_i X_{it} + \alpha_i + u_{it} + \varepsilon_i \tag{6}$$

The random effect model assumes: $cov(X_{it}, \alpha_i) = 0$, the composite error of $\alpha_i + u_{it}$ is uncorrelated with the exploratory variables but is serially correlated for observations coming from the same *i*. Random effects assume that the entity's error term is not correlated with the predictors which allow for time-invariant variables to play a role as explanatory variables.

In choosing between the random effect (RE) and fixed effect (FE) models, the standard Hausman test is first applied to determine whether unique errors are correlated with the regressors. If no correlation is found, the RE model is selected. The results of the Hausman test, shown in Table 9, suggest that the RE estimation method is appropriate for this analysis. The selection of variables is informed by insights obtained from interviews with DCC companies and MDEC representatives, as outlined in Table 6. It is important to note that the interpretation of the model here focuses primarily on profitable firms. By limiting the analysis to firms with positive profits, the study aims to understand the factors influencing the performance of financially successful companies.

---

[16] FE assumes correlation between industry's error term and predictor variables while RE assumes otherwise.

Table 9. Impact of grants on profits

	General	Spillover
Equation	(1) *Log* Profit	(2) *Log* Profit
Log BCI	0.362*** (3.43)	0.413** (2.87)
Log DC3	0.666** (2.70)	0.783* (2.49)
Log DCF	0.521* (2.52)	0.247 (1.19)
Log MAC3	0.487** (3.17)	0.547** (2.64)
Log MAC3 co Pro	-1.805*** (-3.49)	-1.668** (-2.87)
Log Export share	-0.0385 (-0.39)	-0.0426 (-0.30)
Log R&D expenditure	0.218* (2.25)	0.430*** (3.33)
Log Labour productivity	0.176 (1.01)	
Log Foreign skilled workers		-0.242 (-1.90)
_cons	0.476 (0.22)	-0.239 (-0.12)
N	124	94
Hausmann test		
Prob>chi^2	0.5465	0.7175
Panel data estimator	Random Effect	Random Effect

Notes: Levels of significance – * p<0.05, ** p<0.01, ***p<0.001. Year dummies are not reported.

The findings in Table 9 (Equation (1)) indicate that a 1% increase in BCi2 grant support leads to a 0.36% increase in profit growth. DC3 grants result in a 0.66% increase, DCF grants in a 0.52% increase, and MAC3 grants in a 0.48% increase. Notably, the DC3 grant, despite being smaller in size but disbursed more frequently, has the most significant profit impact. This suggests that smaller grants, when paired with effective developmental programs and guidance, may be more impactful. Interestingly, MAC3 Co-Production grant recipients did not experience a profit increase, with a potential decline in profit by 1.8%. Interviews suggest that this negative impact is likely due to implementation issues, such as strict clawback clauses, unfavourable terms, and instances where partners withdrew or local studios were unable to complete their work. Differences in tax structures and unclear cross-border agreements may also hinder the benefits of co-production. Some companies argued that co-production activities are considered lower in the value chain, with foreign partners retaining the more valuable intellectual property (IP). One company who has formed a merger with foreign partners stated that after the acquisition, the Malaysian office merely functioned as a sales office (Interview, 2020).

This should not, however, be interpreted as a negative view of co-production with foreign partners. Interviews with companies underscored the importance of foreign partnerships and joint ventures. These collaborations offer several advantages, including positioning Malaysia as a regional production hub, exposing local talent to international production practices, facilitating innovation and technology transfer, and expanding market access. The finding here merely suggests that there is a need to improve on how to harness the benefits of foreign partnerships through training and knowledge sharing (e.g. one notable example is the *Codemasters Accelerator Program*). Additionally, the results indicate the need for improvements in the terms and conditions of grants from the government to better support these partnerships.

Of all the controlled variables, only R&D expenditure positively affects firms' profits. This is interesting because when R&D is measured as a percentage of sales (in Table 7, it does not register a positive impact on the technical efficiency of sales. This shows that R&D may increase the quality of IP but the quality of IP may not be directly tied to sales. However, it still has an impact on profitability through, for example, improvement in human productivity, cost-reduction process upgrading, etc. One explanation is that spending on R&D may not directly be related to short-term growth in sales.[17] Interviews with 21 key DCC companies showed more than 50% agreed that R&D is expensive and may or may not contribute to the company's sales and profitability. Many were unsure about the risks and were not willing to commit due to financial considerations. 35% believed that R&D is a necessary investment and the scale of this investment should be adjusted according to revenue potential. R&D is also an important market competitive tool to harness new opportunities in the market and therefore is important in the long run. The other 15% were ambiguous in their response stating that R&D is a circumstantial strategy that is only applicable for companies with a strong financial position, and can only be used on a specific area of focus in projects.

To test the robustness of the model, Equation (2) in Table 9 replaces labour productivity with the presence of foreign skilled workers. The results confirm the robustness of the model, as 5 out of 6 variables showed consistent results. However, the contribution of foreign skilled workers was not statistically significant, possibly due to the maturing local market and the rising number of local skilled workers. Foreign workers may also be perceived to increase company costs in terms of hiring and salary, hence affecting overall profitability. However, interviews with key DCC companies provided further insights on this matter. Only 23% perceived foreign workers are not significant in contributing to the success of local companies − stating that foreign partners only wanted the funding and benefits from local companies. The majority 70% however, believed that foreign skilled workers contribute significantly to the success of their companies. Foreign skilled workers can multi-task and contribute to technical

[17] https://www.forbes.com/sites/tendayiviki/2016/08/21/why-rd-spending-is-not-a-measure-of-innovation/?sh=26547651c77d

solutions – an area where local skilled workers are in deficit. Some local junior staff also experienced mentoring from foreign knowledge workers.

Evidence of horizontal spillovers is visible where local ex-employees trained by a foreign firm started their own companies, hence improving the production frontier of local firms in general.[18] Unfortunately, the total number of foreign skilled workers in the industry is small to begin with, hence it may be difficult to quantify the impact of their contributions (which may also be the reason for the statistical insignificance in the model).

5. Conclusion and Policy Recommendations

The DCC industry in Malaysia is maturing, with several key features identified in this study: strong domestic and international demand, a high skill and technology-driven workforce, significant job creation (particularly for local skilled workers), high domestic value-added content, and its emerging role as a source of economic growth within the expanding digital economy. Over the years, the government has played a crucial role in overseeing the industry's development. Notable success has been seen particularly in the games and animation clusters, likely driven by government grants. One policy suggestion is to build on the success of these industries, expand and create new clusters within their value chains.

The findings in Table 9 (Equation (1)) show that a 1% increase in BCi2 grant support to a company leads to a 0.36% increase in profit growth. The DC3 grant had a 0.66% increase, DCF 0.52% and MAC3 0.48%. This indicates that DC3, despite its smaller fund size (but more frequent disbursements), has the most significant impact on profits. The result suggests that smaller grants are more effective when paired with strong developmental programs and guidance. Based on this evidence, future grants should incorporate knowledge-sharing requirements from successful recipients, with an emphasis on mentoring as a key component.

An interesting finding is that MAC3 Co-Production grant recipients did not show an increase in profit growth, with some even experiencing a decline in profit by 1.8%. Interview results suggest that this is more likely due to implementation issues rather than the program itself. Policies and trade agreements need to address differences in tax structures between countries involved in co-production. Unclear cross-border agreements in digital services trade and co-production treaties, such as ambiguous rebates on activities completed in another location, may have diminished the benefits of the grant.

Some companies also argued that co-production activities tend to occupy the lower end of the value chain and yield lower margins for Malaysian partners. The more valuable intellectual properties (IPs) are typically retained by foreign partners, while local companies are tasked with lower-end roles such as pre-production, post-production and commercialisation. One company that had merged with a foreign

[18] https://www.investkl.gov.my/Relevant_News-@-UK-based_Codemasters_has_aggressive_plans_for_its_Malaysia_studio.aspx. The UK-based Codemasters studios is a highly reputable company and is the longest operating AAA studio in Malaysia.

partner reported that, following the acquisition, its Malaysian office was reduced to functioning solely as a sales outlet. A recommended policy improvement is to revise future co-production grant application forms to require clear articulation of responsibilities, expected learning outcomes and potential spillover benefits − such as enhanced market access and training opportunities.

The lack of talent remains a recurring issue in Malaysia's DCC industry. Although not directly reflected in the empirical findings, interviews suggest that the current pool of human capital is insufficient to meet the demands of this skills-oriented sector. Companies frequently cited challenges in attracting and retaining a skilled workforce as major barriers to industry growth. Structural issues have persisted over the years, including a mismatch between the skills supplied by academic institutions and those demanded by the industry. Policies promoting longer internship programs for university students could help equip graduates with relevant practical skills. Additionally, educators should stay informed of evolving industry trends and technologies to ensure the relevance of their teaching. Supporting industrial training opportunities for lecturers/trainers could further help align academic curricula with industry needs.

Local DCC companies face limited exposure to international content trade markets and often lack the necessary knowledge, networks or access to global market opportunities. This restricts their ability to scale, collaborate or commercialise content beyond domestic borders. To overcome these challenges, policy support is needed to enhance digital integration and global connectivity. This includes facilitating cross-border collaboration, streamlining trade processes and harmonising international regulatory frameworks relevant to digital content. Extended bilateral or regional initiatives in new regions, such as the Middle East and North Africa (MENA), can take various forms including co-production agreements, market access partnerships and digital trade pilot programs. These initiatives can serve as effective platforms to gradually build international experience and enhance the global competitiveness of local firms.

References

Aigner, D., Knox Lovell, C.A., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21−37. https://doi.org/10.1016/0304-4076(77)90052-5

AuYong, H.N. (2018). *Making full use of a creative economy: Review of the development of Malaysia as a hub for creative content technologies*. Paper presented at the 2nd Conference on Technology & Operations Management (2ndCTOM), 26–27 February 2018, Universiti Utara Malaysia, Kedah, Malaysia. https://repo.uum.edu.my/id/eprint/24192

Battese, G.E., & Coelli, T.J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis, 3*(1–2), 153–169. https://doi.org/10.1007/BF00158774

Battese, G.E., & Coelli, T.J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*(2), 325–332. https://doi.org/10.1007/BF01205442

Bogachev, I. (2023, May 16). How the growing creative economy will soon devour the real economy. *Forbes*. https://www.forbes.com/sites/forbestechcouncil/2023/05/16/how-the-growing-creative-economy-will-soon-devour-the-real-economy/?sh=750de89e74bc

Bronzini, R., & Piselli, P. (2016). The impact of R&D subsidies on firm innovation. *Research Policy. 45*(2), 442–457. https://doi.org/10.1016/j.respol.2015.10.008

Choi, D.O., & Oh, J.E. (2009). Efficiency analysis of the digital content industry in Korea: An application of order-m frontier model. In J.D. Lee, & A. Heshmati (Eds.), *Productivity, efficiency, and economic growth in the Asia-Pacific region* (pp. 299–313). Contributions to Economics, Physica-Verlag HD. https://doi.org/10.1007/978-3-7908-2072-0_15

Clausen, T.H. (2009). Do subsidies have positive impacts on R&D and innovation activities at the firm level? *Structural Change and Economic Dynamics, 20*(4), 239–253. https://doi.org/10.1016/j.strueco.2009.09.004

Colombo, M.G., Giannangeli, S., & Grilli, L. (2013). Public subsidies and the employment growth of high-tech start-ups: Assessing the impact of selective and automatic support schemes, *Industrial and Corporate Change, 22*(5), 1273–1314. https://doi.org/10.1093/icc/dts037

Criscuolo, C., Martin, R., Overman, H.G., & Reenen, J.V. (2019). Some causal effects of an industrial policy. *American Economic Review, 109*(1), 48–85. https://doi.org/10.1257/aer.20160034

Davies, P. (2012). The state of evidence-based policy evaluation and its role in policy formation. *National Institute Economic Review, 219*(1), R41–R52. https://doi.org/10.1177/002795011221900105

Economic Planning Unit (EPU) Malaysia. (2021). *Twelfth Malaysia Plan, 2021–2025: A prosperous, inclusive, sustainable Malaysia*. Percetakan Nasional Malaysia Berhad.

Google, Temasek, Bain. (2020). *e-conomy SEA 2020 – At full velocity: Resilient and racing ahead* (5th edition of e-Conomy SEA). https://www.bain.com/globalassets/noindex/2020/e_conomy_sea_2020_report.pdf

Greene, W. H. (1980). On the estimation of a flexible frontier production model. *Journal of Econometrics, 13*(1), 101–115. https://doi.org/10.1016/0304-4076(80)90045-7

Hall, B.H., & Maffioli, A. (2008). Evaluating the impact of technology development funds in emerging economies: Evidence from Latin America. *European Journal of Development Research, 20*, 172–198. https://doi.org/10.1080/09578810802060819

Hottenrott, H., Lopes-Bento, C., & Veugelers, R. (2017). Direct and cross scheme effects in a research and development subsidy program. *Research Policy, 46*(6), 1118–1132. https://doi.org/10.1016/j.respol.2017.04.004

Howell S.T. (2017). Financing innovation: Evidence from R&D grants. *American Economic Review, 107*(4), 1136–1164. https://doi.org/10.1257/aer.20150808

Jondrow, J., Lovell, C.A. K., Materov, I.S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics, 19*(2–3), 233–238. https://doi.org/10.1016/0304-4076(82)90004-5

Kam, A.J.Y. (2016). Death of linkages in host countries? A firm-level study on the channels of productivity spillovers in the Malaysian manufacturing sector. *Asian-Pacific Economic Literature, 30*(1), 65−79. https://doi.org/10.1111/apel.12135

Korea Creative Content Agency (KOCCA). (2018). *2017 survey of overseas content market trends*.

Kumbhakar, S.C., Wang, H.-J., & Horncastle, A.P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*. Cambridge University Press. https://doi.org/10.1017/CBO9781139342070

Lee, L.-F. (1983). A test for distributional assumptions for the stochastic frontier functions. *Journal of Econometrics, 22*(2), 245–267. https://doi.org/10.1016/0304-4076(83)90102-1

Liu, Z. (2021). The impact of government policy on macro dynamic innovation of the creative industries: Studies of the UK's and China's animation sectors. *Journal of Open Innovation: Technology, Market, and Complexity, 7*(3), Article 168. https://doi.org/10.3390/joitmc7030168

McKenzie, D. (2017). Identifying and spurring high-growth entrepreneurship: Experimental evidence from a business plan competition. *American Economic Review, 107*(8), 2278–2307. https://doi.org/10.1257/aer.20151404

Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18*(2), 435−444. https://doi.org/10.2307/2525757

Michalek, J., Ciaian, P., & Kancs, D. (2015). Investment crowding out: Firm-level evidence from northern Germany. *Regional Studies, 50*(9), 1579–1594. https://doi.org/10.1080/00343404.2015.1044957

Nurse, K. (2021). The digital creative economy and trade: Strategic options for developing countries. In M. Smeets (Ed.), *Adapting to the digital trade era: Challenges and opportunities* (pp. 254–273). World Trade Organization.

Organisation for Economic Co-operation and Development (OECD). (2002). *Tax incentives for research and development: Trends and issues*. OECD Publishing.

Pokarier, C.J., & Tamiya, Y. (2007). *'Brand Japan' and the internationalization of Japanese creative industries*. Paper presented at the 15th Biennial Japanese Studies Association of Australia, Australian National University, 14th July 2007. https://doi.org/10.2139/ssrn.1560506

Srhoj, S., Škrinjarić, B., & Radas, S. (2019). Bidding against the odds? The impact evaluation of grants for young micro and small firms during the recession. *Small Business Economics, 56*, 83–103. https://doi.org/10.1007/s11187-019-00200-6

Tsai, H.-H., Lee, H.-Y., & Yu, H.-C. (2008). Developing the digital content industry in Taiwan. *Review of Policy Research, 25*(2), 169–188. https://doi.org/10.1111/j.1541-1338.2007.00317.x

World Bank. (2017). *Global investment competitiveness report 2017/2018: Foreign investor perspectives and policy implications*. http://documents.worldbank.org/curated/en/169531510741671962

Yecies, B., & Shim, A. (2018). South Korea's creative industry markets: Looking beyond 2020 to a rising creative economy. In L. Lim & H-K, Lee (Eds.), *Routledge handbook of cultural and creative industries in Asia* (pp. 256–269). Routledge.

Zhou, X., Wang, Z., & Wang, J. (2024). Government support, director characteristics, and innovation performance: Evidence from China's digital creative industry. *International Journal of Technology Management, 94*(2), 271–290. https://doi.org/10.1504/IJTM.2024.135726

Appendix 1. All variables

Independent samples test

		Levene's test for equality of variances		t-test for equality of means					95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
Growth (G) in total sales	EVA	8.086	.004	1.595	3340	.111	42.02713	26.34581	-9.62843	93.68269
	EVNA			1.275	702.736	.203	42.02713	32.96329	-22.69121	106.74546
G in local sales	EVA	.312	.576	-.312	3340	.755	-32.21543	103.09522	-234.35160	169.92075
	EVNA			-.528	2336.726	.598	-32.21543	61.04591	-151.92522	87.49436
G in export sales	EVA	2.459	.117	.852	3340	.394	72.91200	85.61613	-94.95337	240.77737
	EVNA			.655	687.257	.513	72.91200	111.32775	-145.67132	291.49532
G in total jobs	EVA	29.632	.000	2.893	3337	.004	12.42608	4.29566	4.00369	20.84848
	EVNA			2.068	662.158	.039	12.42608	6.00744	.63016	24.22201
G in local knowledge worker (KW)	EVA	28.351	.000	2.192	3337	.028	9.35864	4.26977	.98701	17.73026
	EVNA			1.664	682.549	.097	9.35864	5.62333	-1.68247	20.39974
G in foreign KW	EVA	11.617	.001	1.412	3337	.158	7.48941	5.30355	-2.90913	17.88795
	EVNA			1.523	910.989	.128	7.48941	4.91714	-2.16083	17.13966
Share in R&D sale	EVA	20.513	.000	2.297	3337	.022	18.22593	7.93375	2.67042	33.78143
	EVNA			1.053	578.155	.293	18.22593	17.30643	-15.76522	52.21707
Share in local sales	EVA	18.395	.000	.029	3338	.977	.06162	2.13011	-4.11484	4.23807
	EVNA			.030	859.091	.976	.06162	2.07980	-4.02047	4.14370
Share in export sales	EVA	18.692	.000	.045	3338	.964	.09494	2.13041	-4.08210	4.27198
	EVNA			.046	859.264	.964	.09494	2.07969	-3.98693	4.17682
Share in local KW	EVA	49.994	.000	5.294	3337	.000	7.96283	1.50419	5.01361	10.91205
	EVNA			4.839	772.590	.000	7.96283	1.64551	4.73262	11.19304

Appendix 1. Continued

Independent samples test

		Levene's test for equality of variances		t-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference	
									Lower	Upper
Share in foreign KW	EVA	14.085	.000	-1.436	3337	.151	-.01367	.00952	-.03234	.00500
	EVNA			-1.800	1132.038	.072	-.01367	.00760	-.02858	.00123
R&D G %	EVA	4.118	.043	1.105	3340	.269	30.08918	27.23083	-23.30161	83.47997
	EVNA			.828	677.524	.408	30.08918	36.35970	-41.30206	101.48042
Salary G %	EVA	1.219	.270	-.686	1901	.493	-124.90605	182.19260	-482.22448	232.41238
	EVNA			-1.278	1637.884	.202	-124.90605	97.76514	-316.66390	66.85181
Share of permanent KW	EVA	32.082	.000	2.840	3337	.005	.05521	.01944	.01710	.09333
	EVNA			2.984	883.502	.003	.05521	.01850	.01889	.09153
Share of contract KW	EVA	136.033	.000	9.282	3337	.000	.09854	.01062	.07772	.11935
	EVNA			7.857	729.356	.000	.09854	.01254	.07392	.12316
G in permanent KW	EVA	1.926	.165	.085	3340	.932	.41530	4.88308	-9.15884	9.98943
	EVNA			.098	995.517	.922	.41530	4.22798	-7.88148	8.71207
G in contract KW	EVA	.013	.910	-.026	3340	.980	-1.04759	41.07830	-81.58877	79.49359
	EVNA			-.049	3216.333	.961	-1.04759	21.51663	-43.23528	41.14010
G in total investment	EVA	1.009	.315	-.517	3340	.605	-1786.97101	3457.38492	-8565.77744	4991.83543
	EVNA			-1.129	2763.649	.259	-1786.97101	1582.73130	-4890.42654	1316.48452
G in permanent jobs	EVA	18.006	.000	1.533	3337	.125	5.39718	3.52026	-1.50490	12.29926
	EVNA			1.361	755.082	.174	5.39718	3.96426	-2.38511	13.17947

Appendix 2. Correlation table

	Profit	BCI2	DC3	Dcf	Mac3	Mac3pro	Export	RND	Lab productivity	Foreign skill
Profit	1									
BCI2	0.0326	1								
DC3	0.1468	0.2326	1							
Dcf	0.1069	0.4403	0.4462	1						
Mac3	0.1316	0.1483	0.2058	0.4049	1					
Mac3pro	0.1069	0.4403	0.4462	**1**	0.4049	1				
Export	0.3476	-0.1389	-0.0080	-0.0884	-0.0104	-0.0884	1			
RND	0.1087	-0.0605	-0.0406	0.0512	-0.2261	0.0512	0.0773	1		
Lab productivity	-0.0991	0.0252	-0.2862	-0.0729	-0.2890	-0.0729	-0.0357	0.1818	1	
Foreign skill	0.0933	-0.0590	-0.1250	0.0564	-0.0588	0.0564	0.1953	0.2123	-0.0107	1