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RESEARCH ARTICLE

Trade-offs to using standardized tools: Innovation enablers or creativity constraints?

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Abstract

Research Summary: In platform ecosystems, the creation of new products is often based on standardized development tools. Complementors often have a choice between either using these tools or creating the functionality themselves. In this paper, we study how the use of standardized development tools is related to the type of products created. By using data on the use of middleware (e.g., game engines) in the console video game market, we show that the use of development tools is associated with products that are less novel but with higher sales on average. We exploit a policy change that affected the ability of U.S.-based developers to hire foreign workers as an instrument for the use of development tools and find further support for these patterns.

Managerial Abstract: When developing new products, firms often have to decide whether they base their technology on preexisting components and standardized tools or develop that technology themselves. In general, it has not been clear how using standardized third-party tools that may be available to all firms in an industry affects the nature of the products that are created. Using data on middleware components, such as game engines, in the console video game industry, this paper shows the use of such standardized tools is associated with the creation of products that are less novel but generate higher sales on average. This is an important strategic consideration for firms, but also for platforms that make decisions regarding whether such tools should be allowed on their platform.

KEYWORDS

enabling technologies, modularity, platform ecosystem, platform governance, standardized development tools

1 | INTRODUCTION

The success of platforms is shaped by the portfolio of complementary products (or complements) available for that platform (Cennamo & Santalo, 2013; Parker & Van Alstyne, 2005). To foster the growth and generativity of an ecosystem of complementary products, platform owners make deliberate governance choices, such as allowing the use of third-party development tools (Evans, Hagiu, & Schmalensee, 2006; Ghazawneh & Henfridsson, 2013; Ozalp, Cennamo, & Gawer, 2018). These tools can help developers simplify the product development process by providing core technological functionality. Existing studies have documented the importance of these tools across a wide range of settings (Furman & Teodoridis, 2020; Kim, 2022; Mannucci, 2017; Von Hippel & Katz, 2002), but there has been little work regarding the product-level outcomes of using such tools. In this paper, we investigate how the use of standardized development tools influences the novelty and commercial success of the products that are created.

A stream of the literature on platform strategy focuses on understanding the decisions that shape the creation of complementary products, both in terms of the absolute number and the types of products created. (Cennamo, 2018; Panico & Cennamo, 2022). Allowing the use of development tools that simplify the creation process is one such decision (Evans et al., 2006; Ghazawneh & Henfridsson, 2013). Sony's “Tools and Middleware” initiative, which allowed the use of middleware such as game engines on the PlayStation 2 platform, is an example of a platform allowing the use of third-party development tools to foster the creation of complements. By contrast, Apple blocking the use of Adobe Flash on its browser and operating systems is an example of a firm that restricts the use of certain tools because they believe it will impact the nature of the complements that are created (Horton & Tambe, 2019; McIntyre, Srinivasan, Afuah, Gawer, & Kretschmer, 2021).[1] Despite the importance of these technologies, and the potential effects of allowing them, there has not been much research examining how the use of these tools impacts the types of products created.

Standardized development tools are a common form of enabling technology—foundational technologies that can form the basis for a variety of new products or innovations (Conti, Gambardella, & Novelli, 2019)—found in software development. Many video games, for example, are based on the Unity or Unreal Game engines, which are development toolkits that provide

[1]Steve Jobs commented on this decision by saying: “*...that letting a third party layer of software come between the platform and the developer ultimately results in sub-standard apps and hinders the enhancement and progress of the platform. If developers grow dependent on third party development libraries and tools, they can only take advantage of platform enhancements if and when the third party chooses to adopt the new features*” (Jobs, 2010).

the basic functionality for creating video games (i.e., character movement, physics, etc.). Relatedly, the majority of mobile applications are built using software development kits (SDKs) that provide a basic functionality that developers would otherwise need to create themselves (Chen, Yi, Li, & Tong, 2022). Similarly, virtually all animated films are now created using digital animation tools rather than being hand drawn (Mannucci, 2017). By using standardized tools, firms can save time and resources that would be spent creating basic functionality and can reallocate these resources to the creation of potentially better products (Garud & Kumaraswamy, 1995; Von Hippel & Katz, 2002). Nevertheless, at the same time, the use of standardized tools requires additional customization to create novel products, making it difficult for companies to differentiate themselves from competitors that may be using the same underlying technology. Within the context of platforms, there has been limited work looking at the impact of standardized tools, despite their widespread use. It is unclear whether the use of these technologies allows complementors to focus on developing more novel content by allowing them to focus on the content layer or constrains creativity by making it more difficult for creators to customize their products.

In this paper, we investigate how the use of standardized development tools relates to the commercial success and novelty of the products that are created for a platform, which are critical determinants of the success of a platform ecosystem (Panico & Cennamo, 2022). In particular, we test the arguments above using data on the console video game industry. We exploit the fact that standardized development tools (e.g., middleware components, such as game engines) only became (officially) available after the year 2000. The gradual adoption of these tools allows us to exploit variation by comparing products generated using them to those created without them, for which developers had to manually design the feature(s) in their games. We controlled for a number of factors such as seasonality, marketing expenditure, the generational maturity of the platform, the availability of other products, and competition in the marketplace. The results show that, on average, the use of these tools is associated with products that are more commercially successful (i.e., greater average sales) but less novel (i.e., more similar to those products that were created earlier). We perform several robustness checks to rule out alternative explanations and demonstrate the robustness of the results.

This paper makes several theoretical and empirical contributions. First, it contributes to the literature on the governance of platform ecosystems (Boudreau & Hagiu, 2009; Panico & Cennamo, 2022; Rietveld, Ploog, & Nieborg, 2020; Wareham, Fox, & Cano Giner, 2014). The decision to allow third-party tools is an important governance decision made by platform owners and ecosystem orchestrators (Chen et al., 2022; Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015; Parker & Van Alstyne, 2018). This has an important platform-level implication: the products created using these tools are likely to be less co-specialized for the target platform(s) (Cennamo, Ozalp, & Kretschmer, 2018; Jacobides, Cennamo, & Gawer, 2018), which might be unfavorable from a platform owner's perspective. This is an important extension of our understanding of how governance decisions, such as allowing the use of enabling technologies (in the form of development tools), influence the complements available within a platform ecosystem.

Second, our results have implications for the strategy of complementors themselves. Competitive strategy at the complementor level is being increasingly studied (Argyres, Nickerson, & Ozalp, 2022; Kapoor & Agarwal, 2017; Miric, Boudreau, & Jeppesen, 2019; Tavalaei & Cennamo, 2021; Tiwana, 2015, 2018). Our results indicate that using standardized components fundamentally shapes the types of products created. This emphasizes the strategic trade-off that complementors face when using standardized technologies and how the nature of product outcomes is shaped by the use of these technological components.

Third, this paper contributes to the literature on tools as enabling technologies (Conti et al., 2019; Furman & Teodoridis, 2020; Kim, 2022; Von Hippel & Katz, 2002). We contribute to this literature by highlighting how these tools, as modular components that may be used across different products and may enable experimentation and economics of-substitution (Garud & Kumaraswamy, 1995), lead to more valuable products but also incur customization costs, which makes it difficult to create products that are truly distinct (Bresnahan & Gambardella, 1998; Conti et al., 2019). In doing so, we provide empirical evidence to support these arguments and show that using enabling technologies is associated with products that are more commercially successful but that may also be less novel or distinct.

Finally, this paper makes a methodological contribution by applying a text-based measure of product novelty. We build on a number of recent papers that have used such methods to quantify innovation (Arts, Cassiman, & Gomez, 2018; Furman & Teodoridis, 2020; Haans, 2019; Hannigan et al., 2019; Kaplan & Vakili, 2015). Our method of text-based novelty detection gets its inspiration from anomaly detection algorithms (Goldstein & Uchida, 2016), and it illustrates the use of another tool that researchers can use when attempting to quantify the extent to which an object is different from those that came before.

2 | LITERATURE REVIEW

2.1 | Platform complements as creative products

Many well-known platform ecosystems are based around creative products, such as music, software, videos, or published work. Products in these industries are characterized by high up-front development costs and low marginal costs (Eliashberg, Elberse, & Leenders, 2006; Peltoniemi, 2015). Often, these markets take the form of "blockbuster" competition, with the majority of sales captured by a handful of products (Epstein, 2012; Tschang, 2007). Products are subject to peak demand periods (Einav, 2007), such as the Christmas period, during which movies and video games experience high demand and "blockbuster" products are typically released.

In a market with such conditions, complementor firms (software publishers in our empirical context) face tension. On the one hand, complementor firms prefer to focus on creating products that have a higher chance of success. On the other hand, they may also want to balance the expression of artistic values with the economics of mass entertainment (Lampel, Lant, & Shamsie, 2000). Specifically, this means that they need to balance the more artistic aims of the "creatives" (e.g., movie writers or game developers) with the more economic aims of the "suits" (e.g., movie producers or game publishers). Within game development, these tensions exist between game developers (both the game development studio and the individual creatives designing the game), who often want to create unique and novel products, and publishers (e.g., Electronic Arts Inc.), who handle the funding and distribution and often want to create products that have blockbuster success.

While creativity alone does not lead to successful products, having a creative orientation is important in shaping the success of products (Im & Workman, 2004). Consumers of creative industry products desire a balance between these two forces: they need some level of familiarity to understand a product and some level of novelty to enjoy it (Cillo, De Luca, & Troilo, 2010). Askin and Mauskapf (2017) show that successful songs draw on previous hits while also displaying a degree of novelty that sets them apart. Another option for firms (especially smaller firms) can be a focus on novelty, as Delre, Panico, and Wierenga (2017) show that film studios with budget constraints (i.e., indie studios) may achieve better performance by focusing on non-mainstream (novel) products that face less competition from larger studios. Therefore, firms often want to offer a portfolio of products, some of which may be more novel and others that may be less novel but more focused on becoming blockbusters (Katila, Piezunka, Reineke, & Eisenhardt, 2021; Tschang, 2007). This combination of novel and blockbuster products may also be beneficial for platforms, as platforms themselves may benefit from avoiding excessive within-platform competition arising from too many similar products (Boudreau, 2012; Cennamo & Santalo, 2013). Below, we elaborate on the steps that platforms may take to regulate the ecosystem of products.

2.2 | Platform governance and optimizing the portfolio of platform complements

Platform governance refers to the rules that a platform or the "ecosystem orchestrator" lays out for all complementors or ecosystem participants (Boudreau, 2010; Tiwana, Konsynski, & Bush, 2010; Wareham et al., 2014). These rules specify how things should be done within the ecosystem and include resources that complementors can access (e.g., software development kits, market reports), permission to use third-party tools, or the entry and participation requirements on the platform (Ghazawneh & Henfridsson, 2013; Jacobides et al., 2018; Wareham et al., 2014). Generally, platforms set governance decisions to simultaneously attract complementors and users (Evans, 2003) and to avoid market failure via unfavorable interactions between complementors and users (Boudreau & Hagiu, 2009). Platforms may want to attract complementors that are blockbuster products with high consumer demand. At the same time, platforms may want to attract novel, diverse complements to distinguish them from other platforms and also to serve a wider range of consumer tastes. More products on a platform and products that appeal to a greater number of users increase demand for that platform; at the same time, a larger installed base of consumers leads to a larger supply of products. The strength of this indirect network effect is often crucial in gaining and sustaining a competitive advantage (Evans, 2003; Rochet & Tirole, 2003).

As a result of these conditions, platforms must often consider the optimal mix of complements available on the platform. Depending on conditions, platforms may want to foster quantity, quality, and diversity of products (Binken & Stremersch, 2009; Cennamo & Santalo, 2013; Gawer, 2014; Wareham et al., 2014). For instance, the life cycle of a platform may shape whether it wants to attract products that are more novel and diverse but appeal to a narrow audience, or products that appeal to a larger number of customers (Cennamo & Santaló, 2019; Rietveld & Eggers, 2018). Similarly, depending on user preferences and network size, platforms may benefit from products that are either more novel or higher quality (Panico & Cennamo, 2022). Relatedly, "blockbuster complements" are particularly beneficial to platform owners when they are exclusive to a single platform, which may be critical to the overall success of the platform (Binken & Stremersch, 2009; Lee, 2013). Simultaneously, platforms may benefit from highly unique products that can help the platform distinguish itself from other platforms (Cennamo & Santalo, 2013).

While platforms may seek to optimize the mix of products available, they face a challenge: the decisions about which products are created are most often in the hands of third-party complementors. Platforms often formulate governance policies with the goal of shaping the types of products that complementors will create, but it is often unclear whether and how this shapes the products that are created. Below, we discuss how the adoption of third-party development tools by platform complementors might affect product outcomes.

2.3 | Standardized tools as enabling technologies

Platforms often provide standardized tools as a way of facilitating product development. These tools might take the form of SDKs, which provide the basic building blocks that complementors need when creating their products. They simplify product development by providing a codebase for complementors to use. Different from other standardized tools that impact compatibility, standardized tools that act as enabling technologies can have a significant impact on a product's functionality and novelty. The decision to provide access to tool providers represents an important governance choice that ultimately affects the success of the entire platform ecosystem. However, in the end, while platforms may allow the use of these tools, individual platform complementors decide whether to build complements based on a particular tool, or to recreate that functionality from scratch.

Despite the widespread adoption of these tools, to our knowledge, existing studies have focused only on how the availability of SDKs affects the number of products created (Chen et al., 2022; Ghazawneh & Henfridsson, 2013; McIntyre et al., 2021). There has been no research into how standardized tools shape the types of products that are created. A growing body of literature examines the impact of tools on the creation of scientific knowledge (Furman & Stern, 2011; Teodoridis, 2018). For instance, Teodoridis (2018) shows that hacking of the Microsoft Kinect tool led to a decrease in the cost of conducting motion-sensing research and hence increased research in motion-sensing. In a more recent paper, Furman and Teodoridis (2020) show that access to the Microsoft Kinect tool not only increased the amount of research on motion-sensing but also improved research diversity by inducing changes in the type of knowledge produced. The majority of these studies focus on the impact of tools on the creation of academic knowledge rather than on products that are marketed to consumers. In the present paper, we focus on the use of standardized development tools and on how they shape the novelty and commercial success of the products created.

It is important to acknowledge that the literature on knowledge recombination (often based on backward citations of patents) has linked the source of knowledge to the types of innovations being created (Arts & Veugelers, 2015; Fleming & Sorenson, 2001). These studies are related to the focus of our paper, but, are also substantively different. We focus on reusing existing tools (modular components). This is different from citation-based metrics of knowledge reuse because, in citation-based measures, two different technologies from the same domain are considered to be the same technological input. In this paper, we focus on an enabling technology that is used across products, with the alternative choice being the manual recreation of the same technological functions (Carnabuci & Operti, 2013; Kuhn, Younge, & Marco, 2020). Therefore, while choosing whether to build on existing modular technological components is a potentially important determinant of innovation, it would not be captured by patent-based metrics.

2.4 | Enabling technologies, commercial success, and product novelty

Innovation and new product development are often based on enabling technologies that provide a basic technological foundation and are applicable to a variety of downstream uses or markets (Bresnahan & Gambardella, 1998; Bresnahan & Trajtenberg, 1995). In certain cases, there are even markets for these intermediate (i.e., enabling) technologies, where some companies specialize in developing tools that can be used by others to create consumer-facing products (Gambardella, Heaton, Novelli, & Teece, 2021). The logic is that the specialized companies that provide these enabling technologies (i.e., tools) are able to divide the high fixed cost of creating such tools across a large number of downstream customers who will use those tools to develop subsequent products. Due to the economics of specializing in the provision of such tools ("specializing in generality", Conti et al., 2019), these technologies usual start by serving the largest (sub)markets downstream and then expand to other downstream (sub)markets (Bresnahan & Gambardella, 1998), being much more broadly applicable than the proprietary tools developed by the downstream firms themselves. However, these enabling technologies also face what is termed the "applicability/customization trade-off" (Arora, Gambardella, & Rullani, 1997; Bresnahan & Gambardella, 1998; Gambardella et al., 2021). As such, an enabling technology provides the underlying core functionality that can be applied to a variety of downstream (sub)markets, but it will not be as finely tuned for the application domain as a proprietary custom-built technology would be, therefore requiring additional customization costs depending on the downstream application. An obvious example of such technologies is game engines or game development toolkits in the video game industry (e.g., Unreal Engine or Unity Engine). However, there are examples across a wide variety of industries (Chen et al., 2022; Gambardella et al., 2021; Kim, 2022; Mannucci, 2017).

These intermediate technologies or enabling toolkits are also modular components since they abstract the complexity of the underlying functionalities and provide interfaces to users such that they do not need to know the inner workings of the enabling technology in-depth (Baldwin & Clark, 2000; Von Hippel & Katz, 2002). The literature on modularity has highlighted how modular architectures, which are architectures with components that can be disassembled and recombined in different variations, can potentially influence the creation of products (Baldwin & Clark, 2000; Ethiraj & Levinthal, 2004). Part of the benefit of modular components is that they enable greater experimentation by allowing innovators to more easily combine, and also to recombine existing components (Fleming & Sorenson, 2001; Von Hippel & Katz, 2002). In this paper, we consider a related but unstudied variant of this process: the use of a preexisting modular component that can be built upon versus the recreation of that technology as an integrated part of a new product. In addition to drawing on the modularity literature, the present paper provides empirical evidence for what has largely been considered a theoretical phenomenon (Baldwin & Henkel, 2015; Posen & Martignoni, 2018).

3 | THEORY AND HYPOTHESES

Below, we develop our theoretical arguments around how the choice of using development tools in product development influences product sales and novelty. Certainly, there may be various other factors related to the industry, market maturity, competition, platform demand, or seasonality that influence the demand and novelty of these products, as discussed above (Sections 2.1 and 2.2). We attempt to "hold these factors constant" in our analysis and simply focus on the differences in terms of the use of development tools impacting product characteristics. We further explore implications related to the additional factors mentioned above in the discussion section.

3.1 | Development tools and product novelty

An important outcome of the technological recombination process is the novelty of the output (Arts & Fleming, 2018; Arts & Veugelers, 2015). The specific meaning of a novel product in this case relates to how different or unique a product is from those that have come before, rather than being a determinant of the quality or value of an innovation (Arts & Fleming, 2018; Castañer, 2016).

Building on a modular development toolkit that can be reused across multiple products may influence the novelty of the products being created through several channels. On the one hand, reusing a modular component might allow developers to focus on more creative elements rather than the development of basic functionality. However, while the literature on modularity suggests that such components may allow for greater experimentation, they also impose certain constraints on the types of products that can be created (Fleming & Sorenson, 2001). So, even though modularity helps with experimentation within the solution space provided by the tool, it constrains recombination beyond the compatible components or provided interfaces (Fleming & Sorenson, 2001; Tiwana, 2018). In such cases, it can become difficult and even costly to customize the tool itself to include the features required to create a novel product. This can be regarded as a case in which the tool's use constrains the design hierarchy (Argyres & Bigelow, 2010; Clark, 1985), shifting the solution space to recombination within the defined area (vs. an architectural innovation that also redefines the cross-component connections). This does not mean that developers are unable to modify these tools; rather, they must incur "customization costs" in order to extend the use of these tools for their novel applications. This is consistent with the logic that reusable enabling technologies can be used to create multiple innovations, but customization costs can add up if the technology is used to create innovations that are considered distant from the typical application domain (Arora et al., 1997; Bresnahan & Gambardella, 1998; Gambardella & Giarratana, 2013). There are anecdotes that speak to this from the history of the video game industry. For example, the following quote from the designer of Deus Ex, a prominent video game, reflects this point: "*We had built around the edges of Unreal [game engine] without ever getting too deeply into the nuts and bolts of it. Second, because we didn't know the code inside out, … we tended to be conservative in our approach to modifying it*" (Spector, 2000, pp. 53, 55).

As the arguments above suggest, although we might expect that using middleware components may enable developers to focus on more creative tasks, the customization costs might make it too difficult for developers to greatly modify their products outside of what the middleware components enable. Therefore, products that use middleware components may be similar to other products that use those components. As a result, products based on middleware components are likely to be less novel on average.

> **Hypothesis (H1).** *The use of standardized development tools in product development is associated with products that are less novel (more similar to previously released products).*

The reference or baseline group (for both this and the following hypotheses) is those products that do not use standardized third-party development tools and are constructed by having all the developers write the code themselves (we also account for the few cases where developers/firms create their own tools that can be reused across products within the company).

3.2 | Development tools and commercial success

The use of standardized development tools, such as a game engine or graphics engine, effectively represents a modularization of the development process. These tools can be used and reused as modular components to create different products (Bresnahan & Gambardella, 1998; Garud & Kumaraswamy, 1995; Von Hippel & Katz, 2002). In the literature on modularity, there are several arguments for how being able to use modular components shapes the nature of the products being created. First, utilizing standardized development tools provides the basic building blocks and reduces the time and effort needed to create a basic functionality for a product by writing the code from scratch. As video game insiders noted: "*Having a finished engine helps you focus on what's really important: gameplay*" (Napier, 2000, para. 7).[2] In addition, "*By not having to build your game's engine, you have more freedom to concentrate on your design*" (DeLoura, 2001, p. 2).

Second, modular development through the use of standardized development tools also saves time, as developers are able to overcome the delays that can occur when having to develop the product and the underlying technology itself. These savings in time and resources that would be spent on developing basic functionality can be reinvested in creative work or other tasks that can improve the functionality of the product or to undertake greater experimentation to identify optimal designs (Fleming & Sorenson, 2001; Von Hippel & Katz, 2002).

Additionally, using established tools and components also reduces variability in terms of quality, as these tools are unlikely to contain bugs that would arise if developers were to recreate this functionality themselves (Fleming & Sorenson, 2001). Fixing these bugs would require additional work, or even worse, products could go out to market with bugs, which would dramatically reduce their success. The release of CyberPunk 2077 illustrates how potential bugs can occur when companies develop all of the core code themselves: "*It was riddled with bugs and performance issues when it was finally released…* [The developer] *stretched things too far …. It tried to develop the engine technology behind CyberPunk 2077, most of which was brand new, simultaneously with the game*" (Schreier, 2021, para. 3, 11). All of this would suggest that the use of standardized development tools will be associated with products that are more commercially successful.

One potential counterpoint is that creating a tool for a specific product may result in the loss of the "synergistic specificity," whereby an integrated (i.e., nonmodular) co-specialized design can lead to a higher performing product (Schilling, 2000). For example, developing a product based on a proprietary code developed for a very specific game may mean that it outperforms all others because it is specialized and fine-tuned for that application. Essentially, this is consistent with the idea of having unique assets, which act as isolating mechanisms that allow developers to gain a competitive advantage over potential competitors through superior performance (Wernerfelt, 1984). Therefore, choosing to build on products that are based on the same technology as others, and thus more similar to those products, may result in greater competition and lower potential sales.

[2]Not surprisingly, this quotation highlights the fact that using modular tools also changes the product development process into a modular one where individuals with different tasks (artists and programmers) can work modularly rather than as one awaiting the other to complete the groundwork (i.e., artists waiting for programmers to create the game engine) and can avoid ripple effects where a change in one element may necessitate changes in other aspects of the development process.

In summary, with respect to the impact of middleware on product sales, there are two potentially countervailing forces. On the one hand, by utilizing an established technology, developers can avoid the costly development of basic technologies and instead focus on improving their products. On the other hand, by not using standardized technologies, it becomes easier for developers to create products that are specialized and therefore distinguish themselves from competitors and generate more valuable products. We frame these as countervailing hypotheses.

Hypothesis (H2a). *The use of standardized development tools in product development is associated with products that are more commercially successful.*

Hypothesis (H2b). *The use of standardized development tools in product development is associated with products that are less commercially successful.*

4 | EMPIRICAL CONTEXT, DATA, AND VARIABLES

4.1 | Background: Development toolkits in the U.S. console gaming industry (2000–2007)

Our empirical setting is the console video game industry between 2000 and 2007. This time period corresponds to the sixth and seventh generations of the console market. We chose this context because it was a period that saw the proliferation of game development toolkits, thus providing meaningful variations that we could exploit in this context. Unlike in the PC gaming sector, where game engines were widely available in the 1990s, in the console gaming industry, middleware was not licensed by platforms (although rare ad hoc implementations were observed) until Sony's "Tools & Middleware" licensing program for PlayStation 2, which was launched in 2000. Once a tool was approved by Sony and given a license, it could then be -optionally- used by developers in exchange for a licensing fee paid to the tool developer. These were third-party tools made by entities other than the platform owner or developer of the particular game. Microsoft (Xbox) and Nintendo (GameCube) quickly offered similar approval systems for (almost the same set of) middleware components after Sony's initiative.

Over time, the use of these tools has grown considerably, and today, the majority of modern video games are based on some standardized third-party toolkits. We selected the window from 2000 to 2007, since at this time, middleware components were just diffusing, and there were two types of key components: (a) large middleware components, such as game engines, 3D engines, and graphic engines (these three were mutually exclusive to each other, and over time, they converged to be simply known as game engines, e.g., Unreal Engine), and (b) (relatively) smaller components, which are physics engines (e.g., Havok Engine). We utilize the term middleware to refer to these two broad types of components (game engines and physics engines).

The middleware components that we study in this context are effectively the basic building blocks for a video game. For instance, the Unreal Engine is a tool that provides the basic functionality to implement a character within a physical environment and its movement within that environment (e.g., walking, running, jumping, and interacting), as well as how the objects will be 3D rendered or how lighting reflections will be emulated. Moreover, this particular tool also makes it possible for users to build upon and further customize this basic functionality to provide realistic simulations. By using this tool, developers do not have to write their own codes to create this functionality. Instead, they can focus on composing engaging storylines, developing more detailed and creative graphics or creating more expansive games. However, these tools may be shared across products from different companies, and many products may be based on the same underlying technologies.

We focus specifically on third-party middleware components that are available to any potential developer. Some companies have created their own game engines (e.g., Frostbite by EA), but these were often created for a specific game franchise (e.g., Battlefield series) and then sometimes leveraged across the other games of the company. We account for these in our empirical analysis by controlling for "in-house middleware," which refers to the cases where we can clearly observe that the company leverages its proprietary tools that are clearly branded across multiple games.

Our empirical analysis centers on the comparison of products developed by using these third-party development tools (i.e., game engines and physics engines), in contrast to those that do not use any third-party tools and therefore have to create their own functionality, most likely through employing programmers that will "code up" this functionality.

4.2 | Data sources

We assembled data from multiple sources. First, we collected data on the population of console games from MobyGames. This dataset has been used in earlier studies (Cennamo et al., 2018; De Vaan, Stark, & Vedres, 2015; Mollick, 2012), specifically because of its detailed records of the video game industry. It includes extensive information about the team of programmers and developers that created the game, companies that developed and published the game, and detailed product descriptions describing the content of the game. Finally, it also contains information about game engines, physics engines, and other minor middleware tools (such as those used for video and sound compression, which were widely used and therefore omitted from our analysis). This dataset was combined with detailed sales information from NPD Research that contains the demand (total sales) generated by every title available separately for each platform, as well as the genre information for each game. While we collected data from 1990 to 2012, we selected only the time window from 2000 through 2007 for our analysis, as this was the period during which middleware was introduced before reaching mass adoption (hence, there was meaningful variation in its use). Additionally, this provided us with "slack" observations before and after our sample to account for potential truncation and several years of "lead in" observations to construct our measure of novelty. Our final dataset consisted of 1,112 observations at the title-platform level (e.g., FIFA 2002 for PlayStation 2). This represented only games that were released for Sony- and Microsoft-owned platforms (PlayStation 1, 2, and 3; Xbox; and Xbox 360).[3]

4.3 | Variable construction

4.3.1 | Measure of middleware use

Our measure of middleware is intended to capture the extent to which a product is based on third-party development tools. These middleware components broadly fell into two categories:

[3]We began our analysis with the entire population of MobyGames data between 2000 and 2007. We focused only on console games for PlayStation and Xbox, which were the two most dominant and comparable platforms.

game engines and physics engines, with the former category comprising game engines, graphics engines, and 3D engines (which are mutually exclusively used with each other). Game developers use a game engine and/or a physics engine either by combining a physics engine with a game engine or by using only a game engine. We measured middleware use by the number of toolkit types used in a given game, with the value being either zero (no third-party toolkit used), one (only game engine or physics engine used), or two (both game engine and physics engine used). This reflects the extent to which the code within the game was being created using these middleware components rather than being hand-coded. In the Appendix (Table C4) we provide robustness checks where we vary the way the variable was constructed.

4.3.2 | Measure of product sales (commercial success)

We measured the commercial success of an individual title-platform (e.g., FIFA 2002 for PlayStation 2) based on the total sales (in USD) that the title-platform had in the U.S. market during its lifetime. Since we collected data up until 2012 and our sample ended in 2007, these values did not suffer from truncation (on average, 80% of revenues for a title-platform are generated in its first 12 months). We also validated our results using the total sales in the first 18 months and 12 months after the release of a title on a platform as a robustness check (see Appendix Tables C1 and C2).

4.3.3 | Measure of product novelty

Our concept of novelty is related to quantifying how different a product is from those that already exist in the marketplace. In this definition, we did not assume that novelty translates into greater value or demand, as products that are novel may be of lower quality. To construct this measure, we relied on game descriptions (short textual summaries), which succinctly describe the key elements of a video game.[4] We then used a text-based measure to capture how similar the text of a particular title was to those that currently existed (i.e., those that were previously released).[5]

We drew inspiration from a number of recent studies that had used text-based measures to capture the novelty of innovations (Furman & Teodoridis, 2020; Hannigan et al., 2019; Kaplan & Vakili, 2015). Unlike these studies, which used the distance between topical representations of text documents, we attempted to use a "novelty detection" approach, which identifies whether a text document is in fact different from those that have come before.

We adopted statistical techniques used anomaly detection to identify products that were "novel" (Markou & Singh, 2003; Schölkopf, Smola, Williamson, & Bartlett, 2000). Most text classification problems require prespecifying groups (e.g., Groups A and B) and training an algorithm to distinguish between different observations (characterized by a vector of characteristics). However, there are cases where it is useful to determine whether a particular

[4]Existing studies have measured this on the basis of "tags" or labels from MobyGames. This approach provides a coarser description of a particular game and is subject to bias in the description or categorization of the games in relation to other games. The descriptions used in the present analysis were provided by the Mobygames contributors and used to describe the features of the game.

[5]Importantly, the description does not contain information about the middleware used.

document is similar to or different from the existing data, without having to prespecify a sample of what this different data should look like, as it may be too complex to list all the possible variations. This technique works by fitting a contour (surface) around the training data (data up to the current period, time t) and then checking the position of the test data (from the following period, time $t + 1$) relative to this contour. Observations within the contour can be thought of as describing the area covered by the existing data and, therefore, as being similar to it (i.e., regular or normal observations), while observations outside the contour can be thought of as being different (i.e., irregular, anomalies, or abnormal observations). Additionally, measuring the distance from each point to this contour provides a measure of how close each product is to the "novelty frontier."

Using the software descriptions, we removed punctuation, tokenized the data (removed grammar and suffixes), selected only nouns and verbs, and converted the descriptions into term frequency vectors, with a vector for each unique game title and k terms for the frequency of each word that occurred in the description. This approach ignores word order, meaning, sentiment, and a more complex context. It is what is referred to as a "bag of words" approach.

For each observation (unique game title), we selected all titles that were previously released and then applied our anomaly detection algorithm to fit a contour around the numerical representation of these data. We were then able to specify how tightly the contour fit the data (we used several specifications to ensure that the choice of these parameters did not influence the results). This contour can be interpreted as the "novelty frontier," which defines the boundary for the numerical representation of the data. This was done using a one-class support vector machine with a radial base function kernel. We then compared the focal title to the novelty frontier. If it was outside the novelty frontier, it was considered distinct or novel with respect to products released earlier. If it was within the novelty frontier, it was more similar to the titles released earlier. In Figure 1, we provide an illustration of the novelty frontier with respect to the training data. This approach also provided us with a measure of how far each observation lay from the novelty frontier, which provides a granular measure of the degree of novelty.

We tested the robustness of our results to conventional measures of text distance, such as the cosine distance between the term frequency matrices described above (Appendix Table C1). We performed topic modeling to reduce the dimensionality of the text data (also Appendix Table C1), and we also limited the time window of comparison to titles available on the same platform and within the same genre (Appendix Table C3). Finally, it is potentially important to note that novelty and sales may be related, and we controlled for this in our regressions.

4.3.4 | Control variables

Our control variables included multiple fixed effects (FEs) at the year (release year of game), firm (publisher), platform (console), and product market category (game genre) levels in all models. In some cases, we included more stringent platform-year or genre-year FEs as a robustness check. This approach also allowed us to control for a variety of potentially confounding factors, such as the overall popularity of the platform or genre at that particular point in time (*Genre*, *Platform*, and *Year* FEs). These time-based controls captured much of the variation around the seasonality and popularity of products, as well as the conditions impacting the level of competition among titles within that genre at that point in time. We include FEs at the publisher level (although we tested at the developer level as well), which was the company that hired a programming team to develop the game and take responsibility for its marketing,

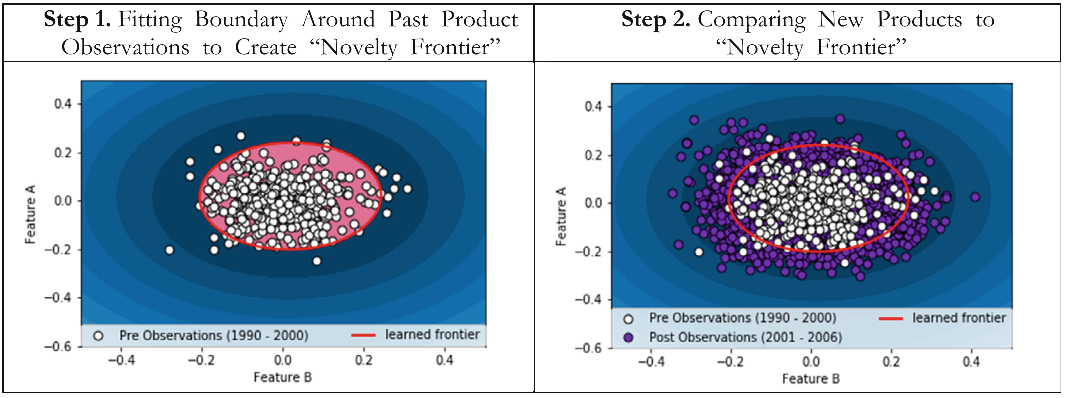

FIGURE 1 Illustration of novelty detection algorithm. Step 1. Fitting boundary around past product observations to create "novelty frontier." Step 2. Comparing new products to "novelty frontier." The novelty detection algorithm used in this paper is based around a one-class support vector machine classifier. This algorithm fits a contour (boundary) based on observations at a time before the current period (i.e., pre-observations). Choosing this boundary has some discretion and we can allow for a certain share of observations to be outside of the boundary (i.e., white dots outside of the learned frontier in (a)). We then overlay (or predict in mathematical terms) whether the observations that come after are within or outside of the learned frontier. Those outside the frontier are considered to be novel, while those inside are considered to not be novel. The novelty score indicates the distance of a particular observation from the boundary of the learned frontier (red circle in the figure)

distribution, and funding (e.g., Electronic Arts). These FEs captured the overall resources that the game development team had and much of the difference in terms of the marketing budget across firms. Additional controls captured the differences within products released by the same firm within the same industry in the same year.

We included *Product Experience* as a control variable, which was the log-transformed number of products that the firm had previously released. We also included *Middleware Experience* as a control variable, which was a log-transformed count of the number of products previously released by the firm that used licensed middleware. Including both variables simultaneously helped to capture the size of the firm and its overall product portfolio, as well as its experience with middleware components (results remained consistent when one of these was omitted).

We also included *Licensed Title*, which was an indicator variable equal to one if the game title used licensed branding or characters from an outside entity. An example of this would be the James Bond-based game "007: Goldeneye," which was built around the James Bond IP, or the NFL game series, which is licensed by the NFL to use the teams and their rosters, as well as NFL branding for the game. This may have shaped both the novelty of the game and its demand, and it was therefore included as a control. *In-House Middleware* was an indicator variable referring to whether the developer was using some proprietary middleware components that they (or their parent company) developed and used across different products. These were not included in our count of third-party middleware tools, as they were not general tools available to all developers. *In-House* was another indicator variable that referred to whether the developer was owned by the publisher of the title-platform (i.e., developer and publisher of the game were under the same parent company). *Project Size* was a log-transformed count of the number of technical and creative credits (i.e., programmers, designers, artists, and engineers) involved in creating the game. This is a common proxy (control) for the budget of the actual game since the primary input for game development is human capital, such as programmers, visual artists, and game designers. This measure has been used in a number of other papers (De Vaan et al., 2015; Mollick, 2012) and reflects the difference in resources between different game titles and, to some extent, between companies making the games. We omitted observations where this measure was not available, as it represented such an important control. In Appendix Tables A1 and A2, we report the descriptive statistics for the variables used in the analysis.

5 | ANALYSIS AND RESULTS

We began by exploring the relationship between toolkit use and product novelty and then the relationship between toolkit use and commercial success (sales). We first reviewed the ordinary least squares (OLS) regression results documenting the relationship between middleware use and these outcome variables. We then tested the robustness of our results by (a) using empirical checks to estimate the magnitude of unobserved selection with respect to causal effects; (b) exploiting the introduction of H1B visa quotas as an instrument that affected whether firms used standardized tools rather than hiring software developers, but which did not directly shape the novelty or demand for video games; and (c) implementing coarsened exact matching (CEM) to ensure we had comparable products when comparing products developed with and without third-party middleware in our analysis.

5.1 | Association between middleware use and product novelty

Our measure of product novelty reflected the distance between any product and the novelty frontier at the time when the product was released. When we stratified this variable by middleware use, we found that middleware use was associated with lower novelty. Approximately 11% of the titles that did not use middleware were outside the novelty frontier (considered novel), while only 3% of the titles that used two middleware components were outside the novelty frontier. This suggests that in the raw data, a strong association could be observed that was consistent with our first hypothesis (see Appendix Figures A1 and A2 for the detailed breakdown).

Next, we move to the regression analysis, where we dealt with a similar comparison but controlled for potentially confounding factors. The outcome variable was the novelty score (distance to the novelty frontier), where positive values indicated greater novelty and negative values indicated lower novelty. We used an OLS regression,[6] and the basic specification was as follows:

$$
\begin{aligned}
NoveltyScore_{i,p} = {} & \alpha + \beta N.\,Middleware\ Components + Controls\gamma + Platform\ FE\gamma \\
& + Category\ FE\gamma + Release\ Year\ FE\gamma + Firm\ FE\gamma + \epsilon
\end{aligned}
$$

The unit of analysis was each title (i) available on each platform (p). This allowed us to include *Platform FEs*, which captured the differences across the main platforms in the analysis

[6]This provides a more reliable analysis than a dummy variable for whether a particular product is beyond the novelty frontier (i.e., novelty = 1 dummy), as there is some subjectivity in the algorithm in terms of where the frontier is located. This depends on parameter choices and the kernel function for the SVM classifier. The novelty score therefore provides a more reliable measure since the relative novelty scores of less versus more novel products will not vary greatly under different model parameters.

(i.e., Xbox and PlayStation). We included FEs for the year when each title was released, as well as dummies for each market category (game genre). These FEs captured the average differences that may have existed across platforms, genres, and general trends in novelty over time. We also included FEs at the company level (publisher), as there are considerable differences across companies in the types of products they create and their access to resources. Our results can therefore be interpreted as demonstrating within-company heterogeneity, as controlling for the company level accounted for differences between companies, and the results can be seen as reflecting differences between products released by the same company. We also included a variety of controls that captured differences between different titles that may have been created by the same company, as explained in the previous section.

The results of these regressions are presented in Table 1. In Columns 1 through 3, we introduce our measure of *N. of Middleware Components* along with release year, publisher, platform, and category FEs, as well as the full set of control variables. These results indicate that the coefficient for *N. of Middleware Components* was negative and associated with a lower novelty score (Table 1, *Column 3*: $\beta = -.003$; $SE = .001$; $p = .002$; $z = -3.06$). It is important to note that this is a within-group effect, as FEs at the category, year, and firm level are included. The standard deviation, within-group, of the novelty score was approximately 0.005. Therefore, a shift from zero to two middleware corresponded to a decrease in the novelty score of more than one within-group standard deviation. This magnitude suggests that while using middleware components does not lead to a substantial difference in product novelty in absolute terms (when comparing all of the products in the entire market, $SD = 0.021$), it does suggest a considerable difference in terms of the products generated by the same company when they use middleware, in comparison to when they do not (the within effect). In Column 4, we replaced release-year FEs with linear and squared time trend controls, which tested whether the results were being driven by a trend in declining novelty over time (as it becomes more difficult to do something different as time goes by within the industry). In Column 5, we replaced *Release Year FE* and *Category FE* with a set of pairs for *Release Year—Category FE*. This further accounted for the results being driven by trends within each genre. The result remains consistent in this specification ($\beta = -.002$; $SE = .001$; $z = -2.00$; $p = .04$). In Column 6, we split the middleware variable into dummy variables for whether one or two middleware components were used, with the use of no middleware components being the baseline category. The coefficient for a single middleware component is quite small ($\beta = -.0007$; $SE = .001$; $z = -.457$; $p = .647$) and indistinguishable from zero, while we observe a much larger negative relationship for products that had two middleware components ($\beta = -.014$; $SE = .003$; $p = .000$; $z = -4.775$). This effect was considerable, as it corresponded to 2.6 standard deviations of the within-group novelty score. This suggests that the use of multiple middleware components was associated with lower novelty scores. In Appendix C, we provide robustness checks with alternative variable constructions. The results remained consistent, suggesting that middleware use was associated with lower novelty scores, supporting Hypothesis 1.

5.2 | Association between middleware use and commercial success (sales)

Second, we look at the relationship between the use of middleware components and product sales measured by the total sales (in USD) for each title platform. We used an OLS regression with the log-transformed product (title platform) revenues as the outcome variable. The basic regression specifications were as follows:

TABLE 1 Results of ordinary least squares (OLS) regressions for product novelty

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline results			Time trends	Year–genre FE	Number of components
N. of Middleware Components	−0.009	−0.003	−0.003	−0.003	−0.002	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
N. of Middleware Components = 1						−0.001
						(0.001)
N. of Middleware Components = 2						−0.014
						(0.003)
Controls						
In-House Developer			0.001	0.000	0.002	0.001
			(0.001)	(0.001)	(0.001)	(0.001)
In-House Middleware			−0.002	−0.002	−0.002	−0.002
			(0.003)	(0.003)	(0.003)	(0.003)
Project Size			−0.002	−0.002	−0.002	−0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Licensed Title			0.001	0.001	0.001	0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Middleware Experience			−0.002	−0.001	0.001	−0.002
			(0.001)	(0.001)	(0.001)	(0.001)
Product Experience			0.000	−0.000	−0.001	0.000
			(0.001)	(0.001)	(0.001)	(0.001)
Multihoming Title			−0.001	−0.001	−0.002	−0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes			Yes
Year Trends (Linear and Squared)				Yes		
Year-Genre FE					Yes	
Genre FE		Yes	Yes	Yes	Yes	Yes
Publisher FE		Yes	Yes	Yes	Yes	Yes
Intercept	−0.015	−0.004	0.003	−1883.878	0.011	0.007
	(0.001)	(0.002)	(0.005)	(527.102)	(0.009)	(0.006)
F	72.17	12.60	11.56	12.639	4.016	11.64
	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.06	0.48	0.49	0.495	0.629	0.25

Note: Unit of observation: Individual title (product)—platform. Outcome variable: Product novelty score (i.e., distance from novelty frontier). Standard errors are reported in parentheses. $N = 1{,}112$. Estimated using OLS regression. Results in Columns 1–3 represent baseline results introducing controls and dummies for *Year*, *Genre* and Publisher. Results indicate an increase in middleware components is associated with a decrease in the novelty score by 0.003 (Column 3: $z = -3.06$, $p = .002$). In Column 4, we replace the time dummies with time trends (linear and squared terms), and in Column 5 we introduce a single dummy variable for each *Year–Genre* pair, rather than the individual components. The results remain consistent (Column 4: $z = -3.12$, $p = .002$; Column 5: $z = -2.00$, $p = .04$). In Column 6, we replace the continuous variable that indicates number of middleware components, with a dummy variable that indicate the number of components. The omitted baseline is the case of zero middleware components (Column 6, N Middle = 1: $z = -.457$, $p = .647$; N Middle = 2: $z = -4.775$, $p = .000$).

TABLE 2 Results of ordinary least squares (OLS) regressions for product value (total sales)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Novelty	Time	Year–genre	Number of
	Baseline results			score ctrl.	trends	FE	components
N. of Middleware Components	0.318	0.354	0.274	0.261	0.291	0.317	
	(0.087)	(0.080)	(0.077)	(0.077)	(0.077)	(0.085)	
N. of Middleware Components = 1							0.295
							(0.093)
N. of Middleware Components = 2							0.486
							(0.220)
Controls							
Novelty Score				−3.675			
				(2.544)			
In-House Developer			0.473	0.478	0.466	0.475	0.473
			(0.076)	(0.077)	(0.076)	(0.086)	(0.077)
In-House Middleware			0.026	0.026	0.069	0.076	0.026
			(0.213)	(0.213)	(0.213)	(0.232)	(0.213)
Project Size			0.393	0.413	0.391	0.390	0.395
			(0.054)	(0.053)	(0.054)	(0.059)	(0.054)
Licensed Title			−0.047	−0.036	−0.069	−0.056	−0.046
			(0.081)	(0.077)	(0.080)	(0.091)	(0.081)
Product Experience			−0.082	0.026	−0.079	−0.056	−0.081
			(0.104)	(0.104)	(0.104)	(0.091)	(0.104)
Middleware Experience			0.165	0.094	−0.079	0.151	0.098
			(0.099)	(0.099)	(0.104)	(0.112)	(0.099)
Multihoming Title			0.134	0.128	0.119	0.021	0.134
			(0.074)	(0.074)	(0.074)	(0.083)	(0.074)
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes			Yes
Year Trends (Linear and Squared)					Yes		
Year-Genre FE						Yes	
Genre FE		Yes	Yes	Yes	Yes	Yes	Yes
Publisher FE		Yes	Yes	Yes	Yes	Yes	Yes
Intercept	15.251	14.982	13.289	13.285	10,387.17	13.426	12.247
	(0.046)	(0.201)	(0.369)	(0.369)	(42,107.77)	(0.687)	(0.490)

$$\log(\textit{Total Sales (US)})_{i,p} = \alpha + \beta N.\,\textit{Middleware Components} + \textit{Controls}\gamma + \textit{Platform FE}\gamma + \textit{Category FE}\gamma + \textit{Release Year FE}\gamma + \textit{Firm FE}\gamma + \epsilon$$

TABLE 2 (Continued)

	(1)	(2)	(3)	(4) Novelty score ctrl.	(5) Time trends	(6) Year–genre FE	(7) Number of components
	Baseline results						
F	13.56	4.51	6.356	6.254	6.86	2.523	6.253
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.14	0.41	0.48	0.51	0.52	0.64	0.53

Note: Unit of observation: Individual title (product)—platform. Outcome variable: Total product sales (log—transformed). Standard errors arereported in parentheses. $N = 1{,}112$. Estimated using OLS regression. Results in Columns 1–3 represent baseline results introducing controls and dummies for *Year*, *Genre* and *Publisher*. Results indicate an increase in middleware components is associated with an increase in revenues (Column 3: $z = 3.57$, $p = .000$). In Column 4, we include the novelty score (distance to the novelty frontier) as an additional control, and the results remain consistent (Column 4: $z = 3.39$, $p = .000$). In Column 5, we replace the time dummies with time trends (linear and squared terms), and in Column 6 we introduce a single dummy variable for each *Year–Genre* pair, rather than the individual *Year* and *Genre* dummies. The results remain consistent (Column 5: $z = 3.58$, $p = .000$; Column 6: $z = 3.57$, $p = .000$). In Column 7, we replace the continuous variable that indicates number of middleware components with a dummy variable that indicate the number of components. The omitted baseline is the case of zero middleware components (Column 7, N Middle = 1: $z = 3.16$, $p = .001$; N Middle = 2: $z = 2.20$, $p = .02$).

We included all the FEs and control variables in the earlier regression. The regression results are presented in Table 2. In Columns 1 through 3, we included the main variables of year, company, genre, and platform FEs. The coefficient for *N. of Middleware Components* is positive ($\beta = .274$; $SE = 0.077$; $p = .000$; $z = 3.57$). This corresponded to an increase in revenue in absolute terms of 27%. While this was relatively large by itself, it also represented 18% of the within-group standard deviation (with firm, industry and time-period FEs), which suggests that there was considerable variability in revenue, even within developer firms and products.

In Column 4, we included the novelty score as an additional control to ensure that the results were not driven by the differences in novelty we found earlier.[7] In Column 5, we replaced the *Release Year FE* dummies with linear and squared time trend controls and with *Year-Category FE* in Column 6, as we did in the earlier analysis. The results remained consistent across the specifications for the *N. of Middleware Components* (Column 5: $\beta = .291$; SE = 0.077; $p = .000$; $z = 3.58$; Column 6: $\beta = .317$; SE = 0.085; $z = 3.57$; $p = .000$). In Column 7, we split the middleware variable into dummy variables for whether one or two middleware components were used, as we did earlier in the previous set of regressions for estimating novelty. The coefficient for the indicator for a single middleware component is positive ($\beta = .295$; $SE = 0.093$; $z = 3.16$, $p = .001$), indicating an increase of 32%, while the coefficient for products that had two middleware components is even larger ($\beta = .486$; $SE = 0.220$; $z = 2.20$; $p = .02$), indicating an increase of 56%. This is consistent with the results indicating that greater use of middleware components was associated with higher revenues. We also reported a variety of additional specifications, including measures of commercial success with critical review scores (Appendix Table C1) instead of revenues, and sales within the first 18 (also Table C1) and 12 months (Appendix Table C2), to account for possible truncation. The results remained consistent. Taken

[7]Interestingly, the correlation between the novelty score and total sales was negative. This is consistent with the finding that, on average, more novel products tend to generate less demand (Fleming & Sorenson, 2001) and the inherent tension in our context between novelty (which is the primary aim of developers) and sales (which is the primary aim of publishers) (Tschang, 2007).

TABLE 3 Results of instrumental variable regressions for both product value and novelty score

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome variable: product novelty score			Outcome variable: product sales		
	Year FE	Time trends	Year–genre FE	Year FE	Time trends	Year–genre FE
N. of Middleware Components	−0.013	−0.011	−0.019	0.916	0.741	1.270
	(0.005)	(0.004)	(0.005)	(0.347)	(0.321)	(0.357)
Controls						
In-House Developer	−0.005	0.001	0.004	0.425	0.431	0.379
	(0.003)	(0.001)	(0.001)	(0.079)	(0.077)	(0.084)
In-House Middleware	0.001	−0.004	−0.007	0.178	0.172	0.336
	(0.003)	(0.001)	(0.003)	(0.221)	(0.215)	(0.229)
Project Size	−0.001	−0.001	−0.001	0.364	0.370	0.335
	(0.001)	(0.001)	(0.001)	(0.054)	(0.053)	(0.057)
Licensed Title	0.002	0.001	0.002	−0.054	−0.071	−0.075
	(0.001)	(0.001)	(0.001)	(0.078)	(0.076)	(0.082)
Product Experience	0.000	0.001	0.000	−0.154	−0.131	−0.124
	(0.001)	(0.001)	(0.001)	(0.107)	(0.105)	(0.114)
Middleware Experience	−0.002	−0.002	−0.001	0.236	0.251	0.245
	(0.001)	(0.001)	(0.001)	(0.102)	(0.100)	(0.106)
Multihoming Title	−0.001	−0.001	−0.000	0.083	0.085	−0.104
	(0.001)	(0.001)	(0.001)	(0.076)	(0.074)	(0.109)
Platform & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Genre FE	Yes	Yes		Yes	Yes	
Year FE	Yes			Yes		
Year Trends		Yes			Yes	
Year-*Genre* FE			Yes			Yes
R^2	0.192	0.224	0.331	0.085	0.107	0.339
F	22.14	33.29	2.25	10.05	14.19	1.922
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First stage F	46.85	53.68	37.03	46.85	53.68	37.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Anderson LM statistic	51.03	57.79	50.77	51.03	57.79	50.77
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Unit of observation: Individual title (product)—platform. Standard errors arreported in parentheses. $N = 1{,}112$. Results for novelty reported in Columns 1 to 3, are consistent with earlier results suggest middleware use is associated with lower novelty (C1: $z = -2.99$, $p = .003$; C2: $z = -2.68$, $p = .007$; C3: $z = -4.07$, $p = .000$). Results for product value (i.e., *log(Sales)*) is reported in Columns 4–6, are consistent with the earlier results suggesting that middleware use is associated with more valuable products (C4: $z = 2.64$, $p = .008$; C5: $z = 2.2$, $p = .021$; C6: $z = 3.58$, $p = .000$). First stage F statistics are above the commonly accepted threshold of 10, suggesting the strength of the instruments. Stock and Yogo critical values (10%) are 16.38 across the specifications, which is considerably lower than any of the first stage F values, further suggesting the strength of the instruments. The Anderson LM chi-squared statistic provides a further test of whether the instruments have sufficient predictive power. The significant test statistic suggests that the excluded instruments are correlated with the endogenous regressor (i.e., *N. of Middleware Components*). Note that we follow a three-step procedure because *N. of Middleware Components* is a count variable. However, this approach only uses a single variable in the 2SLS and therefore does not allow for the construction of a Sargan or Hansen's J statistic.

together, these results suggest that greater middleware use was associated with higher revenues on average, which supports Hypothesis 2a (and does not support Hypothesis 2b).

5.3 | Quantifying the magnitude of unobservables

While we have attempted to control for what may likely be confounding factors, we cannot rule out that there may be other unobservable factors.

We used the Oster (2019) method, which provides a diagnostic statistic (Oster's δ) that indicates how large the selection effect (unobserved factors) would have to be in order to invalidate the statistical effects. This method has been used in a variety of recent papers (Mawdsley & Somaya, 2021; Starr, Frake, & Agarwal, 2019). Oster's δ for the novelty results (Table 1, Column 3) is 7.37, and for the revenue results (Table 2, Column 4), it is 5.51. A rough benchmark is a delta statistic of one, indicating that the selection on observables and unobservables is approximately equal. Our observed Oster's δ values indicate that the unobserved effects would have had to have been more than five times the magnitude of the selection of observables in order to reduce the estimated effects to zero. This provides strong evidence that middleware use had an effect on product novelty and product sales, even though there may have been some unobserved factors.

We used an additional metric developed by Cinelli and Hazlett (2020), which again provides an estimate of how large the unobserved factors would have to be in order to invalidate the results. We calculated the results in relation to a baseline of *Project Size*. *Project Size* was highly correlated with middleware use and the outcome variables. Given that we already controlled for FEs at the category, year, and company level, *Project Size* was a very large predictor of middleware use (more so than any other covariate). The metrics reported (in Appendix Table B5) indicate that unobserved factors would have had to explain more than two and a half times as much variation as *Product Size* in order to invalidate the results for *Product Sales* and more than five times as much variation as *Product Size* in order to invalidate the results for *Product Novelty*. This provides strong evidence suggesting that the OLS results in Tables 1 and 2 are robust.

5.4 | Instrumental variable analysis—Introduction of H1B visa quotas

As an alternative approach to account for potential unobserved factors, we exploited a policy change that made it more difficult to hire programmers and knowledge workers, as this may have affected the decision of companies to use middleware components (middleware being a substitute for tasks performed by programmers) but not the product characteristics directly. We utilized an instrumental variable approach and exploited a shock to the availability of H1B visas introduced by the U.S. government in 2004 (H-1B Visa Reform Act of 2004). H1B visas are an important resource for technology companies, such as game development studios, as they allow them to employ international workers (in fact, H1B visa is the primary way that such companies can employ non-U.S. permanent residents). In 2004, the U.S. government introduced a restriction on the number of visas that could be issued in any given year. Because of this, applications have outstripped the new quota, and H1B visa applications have become costlier, as the results are determined by lottery for commercial companies (i.e., random allocation). We exploited this as an exogenous shift that influenced the use of middleware components (as it affected the ability of firms to hire workers) while not directly influencing the novelty or sales of the video games being created. This policy has been used as a shock in other studies as an exogenous influence on access to human capital (Mayda, Peri, & Steingress, 2018).

To demonstrate that the introduction of the H1B policy was a valid instrument, we performed a number of falsification checks, as suggested by recent studies. This includes the performance of a variety of auxiliary or diagnostic regressions to establish whether there is support for the exclusion restriction. Even though the exclusion restriction cannot be tested empirically, recent studies have suggested checks that researchers can use to lend confidence to their results. We also utilized the "plausibly exogenous" approach of Conley, Hansen, and Rossi (2012) to evaluate whether our results would hold even if the exclusion restriction was violated. Details are provided in Appendix B.

5.4.1 | Data sources for the instrumental variable regression

The U.S. government publishes a list of all H1B employee–employer applicant pairs. We manually matched the list of H1B visa applicants to the companies in our database. We selected only workers who were involved in tasks related to game development, such as programming tasks. This information is also provided in government-published datasets in the form of Standard Occupational Classification codes. We then calculated the number of H1B workers hired by each company and used this as an instrument for the first stage of our analysis.

5.4.2 | Instrumental variable regression analysis and results

In our analysis, the endogenous variable was the number of middleware components used by a particular title. The exogenous instruments were indicators of whether a company used H1B workers, the number of H1B workers employed by the company, and the period after the introduction of the H1B quota in 2004, along with the interactions of these variables. We utilized a 2SLS regression, but because the endogenous variable was a count of the number of middleware components, we had to implement an additional preliminary stage, following the suggestion of Wooldridge (2010, p. 623–625) and Angrist and Pischke (2008, pp. 190–192). In the preliminary stage, we estimated the following:

$$N.Middleware\ Comp_{\{it\}} = \alpha + \beta_1 Post\ Quota + \beta_2 H1B\ Visa + \beta_3 Post\ Quota \times H1B\ Visa \ + \beta_3 N.\ H1B\ Visas + \beta_4 Post\ Quota \times N.H1B\ Visas + \gamma CONTROLS + \epsilon$$

We then extracted the predicted values and utilized them as the instrument in the first stage of our 2SLS regression. This approach was particularly well suited to our purposes, as it allowed us to utilize a Poisson regression in the first stage without violating the assumptions of the IV approach.

We report the results of the first-stage regression in Appendix Table B4. We present the marginal effects in Figure 2, as they are more easily interpretable. Prior to the introduction of the H1B quota, firms that had a higher number of employees on H1B visas were less likely to use middleware components. Following the introduction of the H1B quota, companies that had a

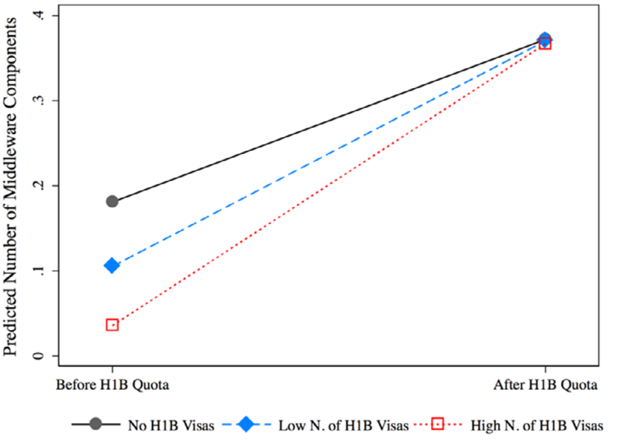

FIGURE 2 Marginal effects for first stage instrumental variable regressions. Marginal effects are estimated based on the first stage of IV regressions. Companies with No N1B Visas include those within the US (where H1B Visas are relevant) and those international which did not rely on H1B visas. Companies with a low number of H1B visa correspond to firms with approximately three H1B visa applications. Companies with a large number of H1B visa applications correspond to firms with approximately 20 H1B visa applications. Only visa applications in the past 3 years considered (moving three-year window) as that is typically how long H1B visas are valid for. Marginal effects indicate that prior to the H1B Quota, those that did not have any employees with H1B visas were on average using 0.18 middleware components per title, while those that had a high number of H1B visas were on average using 0.03 middleware components per title. Following the introduction of the H1B Quota, the use of middleware components for both those with a large number of H1B visas and those that do not, rises to approximately 0.37 components per title

large number of H1B employees became as likely to use middleware components as those that did not. There was an overall greater trend toward greater middleware use over time, which is why there is an upward shift in all groups. These effects are consistent with the idea that prior to the introduction of the H1B quota, firms were more likely to rely on workers instead of using middleware components. However, following the introduction of the H1B quota, it became more difficult for companies to acquire workers, resulting in a greater reliance on middleware components. This implies that our instrument is, in fact, correlated with the use of middleware components. However, there is no reason to expect that this H1B visa quota will directly affect the products being created.

In Table 3, we report the results of the instrumental variable regressions for product novelty (Columns 1–3) and product sales (Columns 4–6). We report the results first with *Release Year FE* (Columns 1 and 4), then with *Time Trends* (Columns 2 and 5), and finally with *Release Year—Category FE* (Columns 3 and 6). The first-stage F statistic of the excluded instruments was above the commonly accepted threshold of 10 across all models and above the Stock and Yogo critical values (10%) of 16.38. Finally, the Anderson–Rubin chi-squared test statistic was also well above the 99.9% threshold for all models, all of which suggest that the instruments were strong predictors of middleware use.[8] One concern is that the *Post Quota* indicator was associated with novelty, as the novelty score decreased over time. For this reason, it is

[8]Because we were following the approach described by Wooldridge (2010, pp. 623–625), we only had a single instrument in the first stage of the 2SLS regression; therefore, we are unable to report the Sargan or Hansen's *J* statistic.

important that we include the controls with time trends, as they were able to account for this correlation over time. The results are consistent with our earlier analysis, suggesting a negative relationship between the use of middleware components and the novelty score (Column 2: $\beta = -.011$; $SE = 0.004$; $z = -2.68$; $p = .007$) and that middleware use was also associated with greater product sales (Column 5: $\beta = .741$; $SE = 0.321$; $z = 2.20$; $p = .021$). It is important to note that the magnitude of the coefficients changes considerably from the OLS regressions. This is consistent with the arguments stated above that the selection effect likely decreased the magnitude of the effects in the baseline regressions. Correcting for this explains why the coefficients are larger in the case of the instrumental variable regressions. The results are consistent across all specifications, providing further support for H1 and H2a.

5.5 | Robustness checks

We sought to ensure that other potential issues were not confounding our results. Therefore, we implemented a variety of other checks, including changing how the sample was defined, constructing the variables, and summarizing the results. We detail these below.

5.5.1 | Matched sample

As an additional check, we performed CEM, and matched the products that used middleware components with those that did not based on the following variables: *Release Year*, *Product Category*, and *Platform*. This ensured that we had a comparable sample of products in our regression analysis. We report these results in the Appendix Table C5. The results are consistent with those reported earlier, suggesting that middleware use was associated with lower novelty ($\beta = -.011$; $SE = 0.004$; $z = -3.06$; $p = .002$). We calculated a similar set of results for product sales and again found evidence supporting our earlier results that middleware use was associated with greater product sales ($\beta = .344$; $SE = 0.182$; $z = -3.06$; $p = .002$).

5.5.2 | Fine-grained controls for developer experience

As argued above, middleware use was found to be highly related to human capital inputs within these organizations. The MobyGames data provided detailed information about the staff behind for a sub-sample of titles; therefore, we exploited this to control for additional factors.

We repeated the analysis but with the inclusion of additional experience controls (see Appendix F), such as *Team Size*, *Average Experience*, and programmer, creative, and marketing teams. We report the results of both the OLS and 2SLS regressions, which did not change in sign or significance. There is evidence that the executive producer team has the biggest influence on product success (Mollick, 2012). In the present study, we had information about the executive producer for 713 titles, and based on this sub-sample, we also controlled for *Executive Producer Experience*, referring to the number of titles where this person was previously executive producer, and for *Executive Producer Past Sales*, where we included the total sales of the titles where that individual was previously executive producer, as this captured whether the executive producer may have been a star based on past success, which might have allowed them to create hit products or otherwise garner more resources from the development company.

5.5.3 | Controls for seasonality and product market concentration

As mentioned in Section 2.1, the video game sector is a creative industry and is thus subject to seasonality, uncertain demand, and other characteristics. While much of this variation was captured by FEs in our main models, we also attempted to control for other potential factors. In Appendix G, we present the results, including controls for the level of competition and seasonality, by controlling for the *Herfindahl–Hirschman index* (*HHI*), *C4*, *Total Product Sales*, and *Total Products Available* within the month prior to release and month of release FEs. The results remained consistent.

5.5.4 | Alternative outcome variables

One concern may be that the results were driven by the specific way in which we constructed the outcome variables. For product novelty, we tested a variety of alternative strategies for constructing outcome variables. First, with the results reported in the Appendix C, we constructed the novelty variable based on the cosine distance between raw text description vectors (Columns 3 and 4) and the cosine distance between Latent Dirichlet Allocation (LDA)-generated topics based on text descriptions (Columns 5 and 6). One additional concern may be that for the majority of the analysis, we compared one product to all products previously released on that platform since 1990. However, in the Appendix C, we also tested whether our results were consistent if we only compared a product to those released in the previous 5 years within the same genre and within the platform. Finally, when constructing these variables, we performed a variety of checks to ensure that our choice of text variables was not biasing our results, including selecting only proper nouns (as they described objects in these video games), lemmatizing (removing suffixes), and stemming (selecting root words). These did not influence the outcome, and we found support for Hypothesis 1 across all specifications.

For commercial success (sales), we tested several different strategies for constructing the regression outcome variable. For the majority of the earlier results, we used the total U.S. sales (USD) of a product. To ensure that our results were not driven by truncation (products released in later periods have fewer observations in which sales occur), we repeated our analysis with the total sales after being on the market for 1 year (see Appendix Table C2). The results were very similar, likely because the majority of sales occur in the first year, and we had more than 3 years of data after our final period of the sample. As an additional check, we used the average critics' review scores from MobyGames as an alternative success variable (on a scale from 0 to 100, where 100 is a perfect rating). The results remained consistent across all specifications, providing support for Hypothesis 2a.

5.5.5 | Alternative sample construction

The sample for our analysis was based on products released on Xbox and PlayStation, as these were the primary platforms where middleware was heavily used, and products on these platforms were in close competition (highly comparable). However, as an alternative, we also repeated the analysis with the omission of PlayStation 1, as there were very few instances of middleware being used on this platform; instead, we added the Nintendo GameCube and Wii platforms, therefore focusing our sample on Generation 6 and Generation 7 consoles. These results are reported in the Appendix Table C7, and they remained consistent for both product novelty and sales.

5.5.6 | Alternative measures of middleware use

As an additional specification, we repeated the analysis but replaced the middleware use variable with indicators that reflected whether the products used game engines and/or physics engines. The results reported in the Appendix indicate that game engine use was associated with lower novelty and higher revenues and that physics engine use was associated with higher revenues, thus providing further support for the earlier results.

5.5.7 | Alternative fixed effects in specifications

In the main set of results, we included FEs at the *Genre*, *Platform*, and *Year* (Release Year) levels. However, as a robustness check, we repeated the analysis by using the combined (pair level) of both *Genre-Year FEs* and *Platform-Year FEs*. In both cases, the results remained consistent, providing support for earlier results.

6 | DISCUSSION AND CONCLUSION

In this paper, we studied how the use of standardized development tools (empirically middleware in the console gaming industry) shaped the products being created. Although the use of enabling technologies such as standardized development tools has become a widespread practice in many platform-based ecosystems (and various industries), it has not been studied how the use of these tools has shaped the products available on the platform. We found that the use of development tools by complementors was associated with products that were less novel but more commercially successful. Our findings suggest that these results may hold even after accounting for potential confounding factors, controls, and potential selection effects.

This paper contributes to the literature on platform governance (Boudreau & Hagiu, 2009; Rietveld et al., 2020; Rietveld, Schilling, & Bellavitis, 2019) and, more particularly, on the relationship between platform openness and generativity (Boudreau, 2010; Cennamo & Santaló, 2019). Our results point to the effect of standardized tools on the nature of products in terms of product sales and novelty. This has strategic implications for both complementors and platforms.

Second, while it is well established that innovation (increasingly) relies on enabling technologies (Conti et al., 2019; Furman & Teodoridis, 2020; Ghazawneh & Henfridsson, 2013; Murray & Stern, 2007; Von Hippel & Katz, 2002), there has been little work examining how the use of enabling technologies shapes the novelty and commercial success of the products being created. This paper contributes to the importance of standardized tools and the implications of using these tools on the innovations that are created, contributing to growing interest in this topic (Furman & Teodoridis, 2020; Kim, 2022).

This paper also contributes to the literature on modularity and innovation (e.g., Ethiraj & Zhou, 2019; Keum, 2020; Zhou & Wan, 2017), as the development tools studied are effectively modular components that may be used across different products. We provide empirical evidence to support the assertion that modular components enable experimentation and the economics of substitution, leading to more valuable products, but these components also incur customization costs, making it difficult to create products that are truly distinct (Bresnahan & Gambardella, 1998; Fleming & Sorenson, 2001; Gambardella et al., 2021).

6.1 | Implications for the trade-off between novelty and commercial success

The results suggest that the use of development tools creates a trade-off whereby companies may opt for either novelty or commercial success. In the creative industry context, this conflict is common because some actors may have financial concerns, while others may have more creative interests (Caves, 2000). Tschang (2007) documents this tension in the gaming industry where publishers are shown to strive to manage development profits, while developers often feel under pressure to preserve their creative freedom (and their aim of achieving novelty).[9] This evidence is consistent with our theoretical arguments and further supports our conclusions.[10] Our study further adds to this picture, highlighting how changes on the technology side (and the overall evolution of product development) affect the tension between creativity and financial success.

6.2 | Implications for platforms and governance

Platform orchestrators make a variety of governance choices regarding the tools that they allow to be used (Benzell, Hersh, Van Alstyne, & Lagarda, 2019; Eaton et al., 2015). Therefore, it is important to consider how these findings at the product level inform the greater discussion around platform governance and interact with economic factors at the platform level.

The dissemination of game engines and other middleware tools in the console gaming industry occurred after Sony created a licensing program ("Tools & Middleware"), which allowed complementors to use approved third-party development tools. Microsoft and Nintendo followed suit shortly thereafter. There have also been counterexamples of platforms preventing access to certain tools. As mentioned earlier, Apple famously blocked the use of Adobe Flash on Safari and its own operating system (iOS) (Horton & Tambe, 2019; McIntyre et al., 2021). Our results show that such decisions might have important product-level effects. However, this is not a direct relationship. Platform orchestrators often choose to allow these tools, but the decision of whether and when to use them is in the hands of the product developers; per our results, this shows that there are trade-offs associated with using these tools.

Additionally, the ramifications of using these tools go beyond the product (i.e., complement). Standardized tools have often been discussed as a way to reduce a particular misalignment between platform owners and complementors (Chen et al., 2022; Ozalp

[9]This observation has also been repeated by industry insiders: "*The motivations of game publishing companies are typically very different from game development firms. Game developers are largely motivated by a love of gaming and a desire to create a new project that outshines and out-innovates anything that has been done before. An interesting new game idea that happens to make a little bit of money is considered a success. Publishers are looking for large returns above all other considerations*" (Reimer, 2005).

[10]Recent studies call for historical evidence as a way of supporting statistical evidence in research (Argyres et al., 2020; Pillai, Goldfarb, & Kirsch, 2021).

et al., 2018). However, our results imply that this may be simply traded for another misalignment for platform owners. Specifically, this misalignment can occur because architecturally complex platforms require co-specialized complements to take full advantage of the underlying platform hardware (see Argyres et al., 2022; Cennamo et al., 2018; Ozalp et al., 2018). However, third-party tools, with their platform-agnostic and modular nature, are less likely to be co-specialized for complex architectures, which could reduce value creation at the ecosystem level (Jacobides et al., 2018). In sum, while creating policies that allow for standardized development tools may increase the number of products on the platform (Chen et al., 2022), such policies may diminish the novelty of these products.

Platform owners may also want to time the decision to allow such tools, depending on their goals for the platform at that moment in its lifecycle. The novelty of the complements may be desirable early in the platform's life cycle because early adopters seek novelty in new platforms, but less so as the platform matures because late adopters prefer predictability within established platforms (Rietveld & Eggers, 2018). Furthermore, if user preferences for innovation diminish as the platform evolves (i.e., the network size expands), complementors may have fewer incentives to invest in innovation in terms of novelty or quality (Panico & Cennamo, 2022). In addition, as discussed above, the demand for creative products has particular peak periods within a year; the pre-Christmas months are the peak in the video game industry. Therefore, it may be in platforms' best interests to consider promoting the adoption of these tools in advance if they hope to align the availability of complements with certain peak periods (see Binken & Stremersch, 2009).

Our study also informs recent literature on complementor strategies. A recent paper by Tavalaei and Cennamo (2021) indicates that complementors are better off focusing either on one product category to exploit potential economies of scale across multiple platforms, or on one platform ecosystem to exploit potential economies of scope across multiple product categories. Given that third-party toolkit adoption helps companies with multihoming, complementors specializing in a specific category may prefer to use these tools more, while companies specializing in platform ecosystems may prefer to invest in resources exclusive to that ecosystem, which would also be in line with the value of co-specialization in ecosystems (Argyres et al., 2022; Jacobides et al., 2018).

6.3 | Limitations and future research

While in this paper we have attempted to account for a variety of explanations and confounding factors, we must acknowledge some limitations. We have chosen to focus on how the use of tools shapes product characteristics in two broad categories: novelty and product sales. However, these effects may be contingent (or may vary) with different product characteristics, such as the generational maturity of the platforms, the level of competition, the maturity of the tools, and incentives to focus on developing different types of products. In our analysis, we have been careful to hold these factors constant to focus on average effects. However, the contingent effects may vary. For instance, we may expect that, early in the generational cycle of a platform, there is a greater taste for novelty; in those cases, there may be fewer products already using standardized tools and, therefore, the novelty effects may be smaller. Alternatively, we may expect that in moments when platforms are trying to grow and therefore are seeking products that are more popular, there may also be benefits to platforms providing these tools.

A limitation of our study is our inability to account for the incentives of individual companies to use middleware components, such as their adjustment and opportunity costs (Argyres et al., 2022); therefore, we have exploited instrumental variables to account for this endogenous process. However, this could serve as a strategic choice that platform complementors can leverage proactively. Future work may investigate the optimal choice of developing products based on standardized components, fully endogenizing the choice based on platform conditions (e.g., platform popularity, generational maturity), complementor market characteristics (e.g., level of competition), and effort that the complementor may want to allocate customizing standardized tools.

We attempted to proxy for the marketing budget and expenditure of developers by using information about the size of the development team, an approach used in a number of earlier papers and the best data currently available. To overcome this limitation, future work may attempt to capture more carefully the assets allocated to marketing and promoting different products.

Empirically, our analysis and framing are focused on the impact of using middleware components while controlling for different types of products, temporal changes, and project resources. Future work may explore other opportunities when studying the interactions between these factors. Our context of a creative industry, together with our main findings, creates two potentially follow-on research questions. First, does increasing reliance on these tools ensure products are released in a timely fashion, such as when targeting periods of peak demand (Einav, 2007)? We expect such a pattern pushes major firms to focus on further commercial success in exchange for novelty (Tschang, 2007). Second, could "indie" firms (those not associated with a large publisher), benefit by focusing their strategy on maximizing novelty? After the time frame of our study, we can observe anecdotally that "indie" or "low cost" development has also become enabled through the availability more modern versions of the tools that we studied, which increasingly resemble "low code" development tools (Dushnitsky & Stroube, 2021). Therefore, it can be worth exploring whether—even though novelty has been reduced on average per game—having these tools leads to a more varied set of firms creating new products and potentially leading to a higher number of very novel products.

It is also important to mention that we are focused on a period when middleware components were first introduced. Modern middleware components are far more sophisticated and therefore customization costs, as well as the costs of building products by writing code have fundamentally changed. As a result, there may be different costs to using middleware components nowadays, as compared to the timeframe of our study which should be considered when generalizing the results.

Finally, our results suggest that developers may benefit from the use of standardized development tools, which can lead to more valuable products. When technological inputs are potentially valuable, will this additional value be captured by the developers using these tools or by the toolkit creators who provide these enabling technologies? Future work might explore these issues theoretically—in terms of who may best capture or create value—and empirically, by exploring the growth of these enabling technologies.

7 | CONCLUSION

In this paper, we demonstrate how the use of standardized development tools impacts the commercial success and novelty of products being created. This is particularly important in relation to platform governance, as platforms often devote considerable attention to optimizing the types of products that complementors develop. These results have implications for the product development strategies of platform complementors who try to maximize novelty, sales, or some combination of both, as well as platform owners who develop policies to allow or inhibit the use of these tools.

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DATA AVAILABILITY STATEMENT

Data used in this study are available from MobyGames and NPD. NPD data contains sales figures for individual titles and restrictions apply to the availability of this data, which was used under license. MobyGames data is publicly available and contains information on individual titles, project development team, text descriptions and middleware components.

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