Standardized Tools And The Generalizability Of Human Capital: The Impact Of Standardized Technologies On Employee Mobility

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Abstract

The mobility of highly skilled knowledge and creative workers is an important determinant of innovation. Existing studies have not considered how the use and diffusion of standardized technologies and tools influence the mobility of individual knowledge workers. We theorize that the diffusion of standardized tools increases the generalizability of human capital and, in turn, increases the ability of individuals to move between companies. Using data on the use of middleware in the console games industry, we find that this diffusion of standardized middleware tools lead to an increase in labor mobility on average, but was associated with higher mobility for individuals with skills that complemented those tools, in comparison to those that were substituted by these tools. Worker experience with standardized tools amplified these effects, as individuals who were experienced in using these tools saw the largest shift in the likelihood of mobility. We do not find that this diffusion led to individuals leaving the industry, but we do find evidence that the diffusion of a common set of tools within an industry was associated with workers being less likely to leave that industry. These results highlight the potential unintended effects of technological standardization and the broad diffusion of standardized tools, which may enable workers to more easily shift between competitors.

1. INTRODUCTION

Human capital is a key resource for organizations and can be a key determinant of firm innovativeness, competitiveness, and survival. Worker mobility directly influences the ability of companies to sustain their human capital, as workers leaving a company to join a competitor often bring skills, knowledge and technologies to the company they are joining to (Campbell, Kryscynksi, and Olson, 2017; Almeida and Kogut, 1999; Wezel, Cattani, and Pennings, 2006; Mawdsley and Somaya, 2016). This is especially important in highly skilled and knowledge intensive settings (Mahoney and Kor, 2015; Raffiee and Byun, 2020) as human capital is especially important for organizational outcomes in these settings.

Labor market frictions, which are constraints to mobility between organizations, can make it difficult for workers to move between employers, allowing companies to retain their valuable human capital (Mahoney and Qian, 2013; Campbell et al., 2017). Existing studies have focused on a variety of factors that may shape labor market frictions, such as the (firm) specificity of the human capital, the existence of complementary assets (Becker, 1964; Coff & Raffie, 2015), and increased mobility costs from intellectual property rules and non-compete contracts (Campbell, Ganco, Franco, and Agarwal, 2012; Starr, Frake, and Agarwal, 2019). However, existing studies have not considered how the use of technology or tools within companies may create or diminish labor market frictions that can influence mobility.

The recent growth of digitalization has been paralleled by the growth of software and tools that automate many high-skill knowledge worker tasks. For instance, in the context of animation, where the creation of new content was traditionally a manual and laborious task, animation software tools have automated and simplified this process (Mannucci, 2017). Similarly, in the context of music recording, software tools have been used to automate labor-intensive workflows (Jeppesen and Frederiksen, 2006). Enterprise software systems have simplified laborious record keeping tasks for doctors and lawyers (Greenwood, Ganju, and Angst, 2019). This is analogous to how computerization, information technology, and software tools automated many tasks in organizations (Nagle, 2019; Bresnahan, Brynjolfsson, and Hitt, 2002; Forman & van Zeebroeck, 2019). With the growing prominence of technologies such as Artificial Intelligence (AI) and blockchain, there is an expectation that there may be many other high-skill knowledge worker tasks that are at least partly automated.

When a new technology automates or replaces tasks performed by workers, it alters the value worker skills within an organization. There are various examples from recent history. For instance, prior to the advent of spreadsheets (or other easy to use calculators), human workers with an aptitude for arithmetic calculations would be hired to perform repetitive calculations. Following the introduction of spreadsheets, which could perform arithmetic calculations with higher accuracy and speed than any "human calculator", the value of individuals that could perform these calculation tasks fell dramatically, but the value of individuals that performed complementary tasks (such as performing analysis with spreadsheets) increased dramatically (Agrawal, Gans, and Goldfarb, 2018). A similar parallel can be seen from the diffusion of computerization and information technology within enterprises over the past several decades (Autor et al., 2003; Bresnahan et al., 2002). When the value of an individual worker's human capital increases, there is in general a greater likelihood that they will change employers, even holding other variables constant[1]. Therefore, we might expect that technological changes may alter the value of workers and create a shift in worker mobility patterns.

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[1] This is a probabilistic argument that is often found in many settings (Swider et al. 2011; Byun et al., 2019). While a worker's current organization may attempt to keep them, in general we would expect to see more mobility on average, when individuals have greater value, as they have greater opportunities for mobility. For instance, Bidwell (2011) finds that external hires tend to perform worse but receive 18% higher wages than workers hired internally. This would suggest that workers with high human capital and the opportunity to switch would be better of switching to competitors, than remaining in their existing company, all else held equal.

A second consideration is that many tools and technologies are not used by a single company, but are diffused and standardized across many companies within an industry.[2] For instance, digital tools and software for animation or programming, are most useful when they are widely used (Duan, Gu, and Winston, 2009; Gallaugher & Yang, 2002; Mannuci, 2017). Similarly, continuing with the example of spreadsheet software, the needs for interoperability and a workforce with a common set of skills led to standardization around a small number of widely used spreadsheet software tools (Shapiro and Varian, 1999; Church and Gandal, 1992). If workers have experience with technologies which are widely diffused, then their skills may become more general and less company specific, making it easier for them to shift to competitors (Raffiee, 2017; Raffiee and Coff, 2016). Alternatively, if workers have experience with idiosyncratic, or company specific technologies, then their skill may be less transferable to competitors. Therefore, the diffusion and standardization of technologies may similarly shape the labor market frictions within an industry (Mahoney and Qian, 2013; Campbell et al., 2017), influencing worker mobility patterns.

In this paper, we study the role of technological diffusion and standardization on the mobility of knowledge workers. We argue that standardized technologies which can automate or replace worker tasks can influence worker mobility in two ways. First, that these technologies shift the value of worker skills, enhancing the value of workers whose skills are complementary to the technology, leading to greater mobility for them, and decreasing the value of workers who are substituted by the technology, leading to these workers' lower mobility. Second, we argue that as this technology diffuses, the skills of workers become less firm specific (as they are based on standardized tools) and therefore workers experience lower labor market frictions and greater mobility.

[2] Here, we want to draw a distinction between patented technologies that firms may have exclusive access to, compared to the more general and diffused third party tools that are the focus of this paper. We are especially interested in these types of tools.

Using data from the console-based video game industry from 1995 to 2010, we study how the diffusion of middleware components, a software development tool that replaced functions performed by human coders, influenced the mobility of workers between companies, and outside of the industry. Our empirical design centers on the fact that middleware components, starting with the Unreal Game Engine, began to diffuse quickly through shooter games (a popular genre focused on an avatar moving through space with a weapon, whether from a first- or third-person perspective), while diffusing much more slowly in other genres. These middleware components are software tools that were used to automate the game development process, replacing tasks previously performed by programmers. We exploit the introduction of those tools to analyze how the diffusion of these components influenced worker mobility, exploring differences for workers with different skillsets and levels of experience. The results indicate three important findings. First, that prior to the diffusion of middleware (i.e., adoption by only a few organizations), the use of middleware components is associated on average with lower mobility, but that following the diffusion of middleware, these effects reverse and individuals working with middleware components experience higher mobility. Second, workers with complementary skills (creatives such as game designers and artists in the context of game development using middleware) experience higher mobility in relation to workers with skills which are substituted by this technology (programmers in the context of game development using middleware). Third, previous worker experience with middleware increases overall mobility, however, this increase is also most pronounced for those workers with complementary skills.

These results present a number of contributions. This paper contributes to the literature on the mobility of knowledge workers (Raffiee, 2017; Byun et al., 2019; Campbell et al. 2012; Agarwal et al., 2004; Franco & Filson, 2006), by considering the role that the introduction, use and diffusion of technologies play in shaping labor market frictions and worker mobility. This is an important but underexplored issue in relation to how the environmental context may shape employee mobility (Mawdsley and Somaya, 2016). Existing studies have documented how technological change may impact the value of worker skills, but have focused primarily on low-skilled workers. The automation studied in this paper relates to the increasingly more common, but understudied case of highly skilled workers becoming automated or substituted by technologies. This paper is part of a growing set of studies that considers the implications of technology on highly skilled workers (Horton & Tambe, 2019; Greenwood et al., 2019). The present study builds on these earlier papers, but considers both technological diffusion and the complementarity of worker skills on worker mobility decisions. This paper also answers a broader call for understanding how technologies shape organizations and forms of organizing (Yoo et al., 2012; Faraj, Jarvenpaa, Majchrzak, 2011), and particularly into regards to emerging technologies such as AI and Blockchain, which promise to grow in importance in the coming years (Von Krogh, 2018; Constantinides, Henfridsson, and Parker, 2018).

2. LITERATURE REVIEW

2.1 Worker Mobility, Knowledge Production and Innovation

Technological innovation is largely a process of recombining and repurposing existing technologies to new and useful ends (Weitzman, 1998; Fleming, 2001). Existing studies have highlighted that for organizations to successfully foster innovation, they must exploit their internal skills and assets, while at the same time they undertake exploratory activities to find new sources of innovation (March, 1991; Taylor and Greve, 2006). One potentially important source of exploratory innovation is attracting workers from other companies that may have novel perspectives and may be able to stimulate innovation (Saxenian, 1994; Rosenkopf and Almeida, 2003; Song et al., 2003; Tzabbar, 2009). The quote by Kenneth Arrow is often regarded important for this phenomenon:

"mobility of personnel among firms provides a way of spreading information" (1962: pg. 615). In fact, recent studies have shown evidence of how mobility between firms can foster innovation (Kaiser et al., 2015; 2018; Somaya, et al., 2008) and provide a source of competitive advantage for receiving firms (Coff, 2010; Campbell et al., 2012), and can be the demise of the originating organizations (Wezel et al, 2006; Campbell et al., 2012).

This perspective largely considers employees as an asset or input that firms can use to create or appropriate value (Barney, 1991; Wernerfelt, 1984; Coff, 1997). A broader literature has considered the role that workers play in capturing and creating value within organizations (Holmstrom, 1999). A chief concern of this literature is that workers may have an incentive to maximize their own utility, rather than that of the company which employs them. This literature highlights a tension between the costs that a company accrues to onboard and train their employees, in relation to the risks they face for the employees leaving and being hired by competitors (Harris & Holmstrom, 1982). The ability of companies to retain valuable employees, effectively relies on labor market frictions (or constraints) that prevent workers from moving easily between companies (Campbell et al., 2012; Mahoney and Kor, 2015; Mawdsley and Somaya, 2016; Campbell et al., 2017). Many of these mobility constraints revolve around the role of knowledge and complementary assets that an employee transfers or uses in undertaking his/her tasks. For instance, employers create frictions through non-compete legislation (Marx, 2009) and being litigious (Ganco, Ziedonis, and Agarwal, 2015) to keep the employees in their organizations. Many employees also deliberately choose positions where they can acquire valuable skills, so that they can be more attractive to potential employers if they decide to change employer (Bidwell & Mollick, 2015; Bidwell et al., 2015).

A key friction long discussed is the firm specificity of knowledge and complementary assets used by the employee. This relates to the question of whether human capital, the skills gained through education or experience, are relevant for a particular employer and their competitors (Becker, 1964; Hatch & Dyer, 2004; Coff and Raffie, 2015). Such specificity is also related to other demand-side frictions highlighted in the literature, such as socially complex shared routines within an organization (and commonly within a team) (Campbell et al., 2014; Mahoney and Kor, 2015), or information asymmetry, which at least partly stems due to difficulty of evaluating employee's quality given only limited amount of an employee's knowledge can be assessed in non-firm specific context (Campbell et al., 2017). Thus, if a worker's skills are highly specific to their employer, they will face more frictions in the labor market, and thus fewer outside options and limited scope for mobility. However, if worker skills are broadly applicable, including to competitors, then workers will have greater opportunities to shift to other companies. One aspect which has not been studied is how the introduction and diffusion of technologies may influence the mobility of workers between organizations.

2.2 Technological Diffusion and Standardization

There are countless examples of "networked technologies" in the modern economy, where the value of the technology increases as they become utilized by a greater number of users (Schilling, 1998; Shapiro and Varian, 1999). A common consequence of such "network effects" is that, while at the start there may be multiple potential technologies, a single technology (generally) eventually dominates and becomes the "standard" for that technology (Katz and Shapiro, 1999; Suarez, 2004). This is increasingly becoming a strategy for many companies that are selling digital tools or technologies, which seek to make their products a "platform" where follow on companies can build on or customize these tools and technologies (Parker & Van Alstyne, 2005; 2017) as to encourage the growth and diffusion of their products. This has led to many technology markets where there is widescale diffusion and standardization around a small number of tools (e.g. Python or R as commonly programming tools, or Unity and the Unreal engine, in video game development tools, AutoCAD and

SolidWorks in drafting software).

There are numerous benefits to this process of technological diffusion and standardization, such as fostering innovation by encouraging companies to build on common technologies (Garud and Kumaraswamy, 1995; Boudreau, 2010; Vakili, 2016) or avoiding costly incompatibility between products (David & Greenstein, 1990; Katz and Shapiro, 1992; Gandal, 1995; Wigand et al., 2014). The diffusion of certain tools may create benefits, such as the growth of a skilled workforce that is familiar with a particular tool. Rock (2019) provides evidence of this phenomenon by showing how the release of TensorFlow, a powerful tool for applying deep learning algorithms, led to the diffusion of skillsets around AI and deep learning. There is a broader related literature that has looked at how tools in an academic setting, such as CRISPR gene editing tools, or the Microsoft Kinect camera, shaped the work of academic researchers as they became more diffused (Teodoridis, 2018; Zyontz, 2018; Nagle & Teodoridis, 2020). Especially in the case of companies, the use of diffused tools may only be desirable if the benefits from a widely diffused technology, as described above, outweigh the potential benefits of having a unique or proprietary technology that may allow companies to differentiate themselves (consistent with resource-based theories of competition, e.g., Barney, 1991). However, existing studies have generally not considered that these diffused tools may make it easier for skilled workers to shift between different companies, potentially making it difficult for companies to retain another important strategic asset, in the form of human capital.

There is a broader literature that has looked at technologies which may be applied to a variety of different application areas (e.g., tasks or even industries) termed as "general purpose technologies" (Jovanovich & Rousseau, 2005; Bresnahan and Trajtenberg, 1995; Arora, Gambardella, and Rullani, 1998; Moser and Nicholas, 2014). These technologies have some parallels to the idea of diffused or standardized tools, as they are general technologies that may be used to create a variety of follow-on innovations.[3] Aghion et al. (2002) consider that the "generality" of these technologies may shape the ability of workers to transfer skills, between different jobs. However, this theoretical paper focuses primarily on the issue of inequality resulting from technological displacement, rather than potential implications for mobility between companies, therefore not providing answers on whether standardized tools may shape the mobility of workers.

3. THEORY AND HYPOTHESES

Tools and technologies are often adopted by companies because they simplify or automate laborious tasks. In the case of spreadsheet software described above, the introduction of these software tools that could automate the arithmetic that went into account keeping and finance replaced and simplified many human capital-intensive tasks. CAD software (Computer-Aided Design) software provided a tool that simplified many drafting and design tasks, which were previously performed by hand by architects and engineers. Relatedly, in the case of video game development, middleware components, such as game or graphics engines, automated much of the lower-level functionality (codebase for basic 3D rendering, visualization, movement, physics, etc.) that simplified software development tasks. However, these tools also altered the value of workers and worker skills as many conventional accounting, engineering or programming skills are no longer in demand as before, while a new set of skills became highly valued.

A common outcome of such changes in the value of worker skills is the decision to change companies (Byun, et al., 2019). On the one hand, the diffusion of tools may make worker skills more general (i.e., less firm-specific human capital) and therefore make it easier for workers to shift between

[3] Similar to these parallels, AI is also considered such a general-purpose technology that could itself grow in scope of application and also drive follow on innovation (Trajtenberg, 2018).

companies. Given that employees may be motivated to appropriate value (maximize their monetary gains in any position), then this would lead workers to become more coveted by outside firms, and lead to an increase in individuals changing companies. In principle, we might expect that companies could attempt to retain their skilled workers, but there is evidence that employees may be able to better appropriate value by shifting between companies (Bidwell, 2011).

It is important to acknowledge that while these tools might influence the value of a particular workers skills, they may also create additional labor market frictions, especially if those tools are not widely diffused, making worker skills highly organization specific. This may make it more difficult for workers to move between companies and therefore, make it more difficult for workers to leave a company and move to a competitor. However, once these technologies diffuse and become widely used by competitors in the same industry, the organizational specificity of worker skills decreases, reducing labor market frictions and making it easier for workers to move to a competitor. The diffusion of technologies also represents a broader, environmental level change where worker is facilitated by the establishment of common language and set of practices surrounding a technology (Mawdsley and Somaya, 2016). Therefore, while prior to the diffusion and standardization of a technology it is unclear whether we would expect that the use of a technology to lead to greater worker mobility, we would expect there to be greater mobility of workers between companies following the diffusion of that technology.

H1. *As standardized tools and technologies diffuse within an industry, there is an increase in worker mobility between competitors in that industry.*

This relationship may be influenced by a variety of factors. One important characteristic is the nature of worker skills (Campbell et al., 2017). As motivated in the earlier section, while these tools may automate certain tasks, the nature of worker skills may also shift. Namely, the skills or tasks which are substituted and replaced by these tools and technologies are expected to become less valuable both to the workers in their current company, as well as for other companies in the marketplace, especially as these tools become diffused.

However, other skills or tasks may be complementary to these tools, and in turn workers with those skills are enhanced in value. For instance, in the case of middleware components, many programming tasks (e.g., laying out basic technical functionality of game, physics of character movement, etc.) were replaced. However, many creative tasks (e.g., designing user gameplay, creating characters and scenes, developing storylines, etc.) were complementary to these middleware tools and likely become more valuable. In part, this change in the value of complementary skills is a common economic pattern when skills become automated (Agrawal et al., 2018), since it becomes more necessary for companies to differentiate themselves using these complementary skills rather than widely available tools or substitutable skills (Barney, 1991). Therefore, the complementary assets which can allow companies to differentiate themselves from competitors, in this case, workers with complementary skills, will become more valuable. Consistent with earlier arguments, we would expect workers with greater value to be more likely to shift to a competitor. Therefore, we expect that as technologies become more diffused, workers with complementary skills will be more likely to switch companies, while workers with more substituted skills will be less likely to switch companies.

H2. *As standardized tools and technologies diffuse, workers with complementary skills will be associated with higher mobility (between companies), while workers with substitutable skills will be associated with relatively lower mobility (between companies).*

The arguments above are based around individual human capital in relation to technology.

However, the magnitude of these effects is likely to be also influenced by the degree to which individual workers have experience with those specific tools. Experience with such tools increases the ability of the focal employee to transfer or recreate routines that are used with the complementary assets, therefore granting advantage to the employee (Campbell et al., 2012). In addition, if workers have considerable experience with a diffused and standardized tool, then their skills may be more general and transferable than workers who have comparatively less experience. However, as with the earlier hypotheses, this may depend on the degree to which the workers skills are valuable or complementary to the technological tool. We might expect that if H1 and H2 hold, that these effects are greater for workers with complementary skills than for workers with skills that are substituted.

H3. *As standardized tools and technologies diffuse, experience working with these standardized technologies is associated with greater mobility (between companies), particularly for workers with complementary skills.*

5. EMPIRICAL CONTEXT, DATA AND SAMPLE

The empirical context used in this study centers on the console-based video gaming industry between the period of 1995 and 2009 (which covers 5^{th}, 6^{th} & 7^{th} generation of video game consoles). We focus specifically on console-based video games because gaming consoles often imposed technological restrictions on how software could be developed (Boudreau & Hagiu, 2009; Cennamo & Santalo, 2013), which meant that prior to 2002, middleware components were not widely used in console based game development.[4] However, from the introduction of the Unreal Engine 2[5] in 2002,

[4] They were used in the development of PC and Mac games which is why we focused only on console games. First official third-party middleware program is initiated by Sony, right after its release of Playstation 2 (see Evans, Hagiu, and Schmalansee, 2006. Chapter 5: PONG).
[5] In 2002, Unreal Engine 2 for consoles have been offered, also through the middleware programs by Sony and other platform owners. Before that, Unreal Engine 1 games have been modified for consoles, but they were more "one-off" cases, whereas Unreal Engine 2 (and further versions) supported multiple-platforms "out-of-the-box".

there was a growth of middleware development tools, particularly in the "shooter game" niche of video games where these early middleware components could be used with only a small amount of customization. In contrast, within other niches, middleware components had to be adapted and customized, which made the adoption and diffusion of middleware components more gradual. This diffusion is shown in **Figure 1**, where we present the share of games using middleware components between Shooter and Non-Shooter Games. We provide a summary of the industry trends in each of the periods (I through IV as indicated in **Figure 1**) between 1995 and 2009, in **Table 1**. Our analysis is based on a comparison between products and developers which use middleware, and those which do not, before and after the diffusion of middleware contrasting worker mobility between products in the shooter niche, in comparison to those in non-shooter niches. We summarize the empirical comparisons in **Table 2**.

Within this context we are generally considering two major types of middleware tools: On one hand, there are game engines, which are a comprehensive tool (e.g. The Unreal Engine), that is: "*the software that provides game creators with the necessary set of features to build games quickly and efficiently… that supports and brings together several core areas. You can import art and assets, 2D and 3D, from other software, such as Maya or 3s Max or Photoshop; assemble those assets into scenes and environments; add lighting, audio, special effects, physics and animation, interactivity, and gameplay logic; and edit, debug and optimize the content for your target platforms.*"[6]. On the other hand, there are also separate tools that provide similar functionality for individual elements in the game development process – such as graphics engines and 3D engines that specialized undertaking rendering, animation, and other visual tasks. Physics engines are tools that simulate real-world physics in scenarios such as car racing or flight simulation. We consider both types

[6] Quote from Unity, Game engines—how do they work?, retrieved from https://unity3d.com/what-is-a-game-engine).

of middleware tools, but focus specifically on the types that were widely diffused.[7]

Creating this functionality by hand would require the detailed work of developing the geometry of the "game world" and the physics and dynamics of the game, manually by the programmer. The adoption of middleware tools provided a way of simplifying and reducing the amount of programmer effort required to create the technological core of the game. Programmers remained a useful input to the game development process, as they would often help develop extensions or modifications to the engine. However, in general the total amount of total amount of programmers required reduced significantly relative to creative staff. (See Footnote 8 for example). Additionally, these tools remained quite general, in that programmers, but more importantly creatives, were able to build on a similar set of technologies across different products.

5.1 Data

We constructed the dataset from a number of sources. Data on the population of games in the video game industry was collected from Moby Games, along with the career histories of workers on those games (which has been used in a large number of previous studies, e.g., Mollick, 2012). This career history captures the key development staff [Executives, Programmers, Creatives, etc.], and is

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[7] While these may seem tools for a niche industry, their products are widely used as can be seen from their market valuation. The owner of the Unreal Engine, Epic Games, is valued over 15 billion dollars (including its famous game, Fortnite). It has such a high valuation because of its engine's general-purpose features allowing it to be used in areas ranging from medicine to architecture. Even the individual middleware tools command considerable market value. Physics middleware company Havok was acquired by Intel for 110$ million in 2007, and Microsoft acquired Havok from Intel for an undisclosed amount in 2015.

[8] This anecdote from the Deus Ex's postmortem, from a 2000 critically acclaimed PC game based on the first Unreal Engine (which were not used for our consoles), summarizes the shifting role of programmer and customization issues succinctly: "The Unreal Tournament code we ended up going with provided a solid foundation upon which we were able to build relatively easily. Dropping in a conversation system, skill and augmentation systems, our inventory and other 2D interface screens, major AI changes, and so on could have been far more difficult… The dollars and cents of the deal were right, and I didn't have to hire an army of programmers to create an engine… [W]e were able to make what I hope is a state-of-the-art RPG-action-adventure-sim with only three slightly overworked programmers, which allowed us to carry larger design and art staffs than usual.", retrieved from https://www.gamasutra.com/view/feature/131523/postmortem_ion_storms_deus_ex.php

collected from the information on the back of video game cases (analogous to movie credits).[9] We matched data on the commercial success of these titles using proprietary sales data from the market research firm NPD. Data on middleware components was combined from Moby Games as well as hand collected from other sources. To construct control variables for developer gender and ethnicity we used machine-based classifiers trained on census data.

5.2 Variables

The data for the analysis is at the level of individual project – person pairs (e.g., the list of projects that each individual developer works on). We identify an individual worker mobility event as: any time when a worker changes their employer organization (i.e., video game development firm) as they move between projects. These developers are the employer of the individual worker while engaged on a particular project. When workers complete a project, they often shift to another project within the same developer firm (Tschang, 2007). Middleware projects are defined as those projects that used 3rd party middleware components, such as Unreal Game Engine or Havok Physics Engine. Experience, both total game development experience and middleware component use experience, is calculated based on the number of past projects the developer has worked on. Project size captures the number of people working on a particular project. The Total Game Sales captures the total revenue (Sales USD) generated by that project after the market. These variables help to proxy for projects which were of higher quality, or bigger, which may influence mobility. The specific construction for these variables is detailed in **Appendix A - Table A1**.

5.3 Analysis

The focus of our analysis is based on a comparison between shooter and non-shooter games,

[9] It was a common practice in the console video game industry to list the staff in the physical manual, and more recently, within the game (either through the options menu or upon completing a story-based game).

as defined by the "supergenres" as provided by the NPD dataset, before and after the diffusion of middleware following 2002 (Indicated by the *Post Middleware* variable). To reiterate, the rationale for this comparison, is that middleware components became widely diffused within shooter categories, but less so within Non-Shooter categories. (See Table 2 for a summary) Therefore, following the diffusion of middleware, it became easier for workers to shift between different companies within the shooter niche. The main analysis for individual mobility **(H1)** is based on the following regression model.

$$Pr(Employer\ Change) = \alpha + \beta_1 Shooter + \beta_2 Middleware + \beta_3 Post\ Middleware\ (Post\ 2002) + \beta_4 Shooter \times Middleware$$
$$+ \beta_5 Shooter \times Post\ Middleware + \beta_6 Middleware \times Post\ Middleware$$
$$+ \beta_7 Shooter \times Middleware \times Post\ Middleware + \boldsymbol{C} + \varepsilon$$

The coefficients in the econometric specification can be thought of in relation to a difference-in-differences specification.[10] The baseline terms β_2 and β_4 capture the degree to which the use of middleware affected individual mobility prior to the diffusion of this technology for non-shooter and shooter games. The three-way interaction, β_7, captures the degree to which mobility was greater in the shooter games following the diffusion of this technology, while the other terms capture differences between the groups. We also include a set of control variables (**C**) including, developer firm FE, year FE, platform FE as well as dummies for gender, ethnicity, and experience, number of platforms, project size and total project sales (USD) variables.

To test **H2** we stratify our analysis by the sample of creatives and programmers, which are the

[10] Our specification is analogous to a diff-in-diff in terms of how we use interactions with a "Post" period variable, but in our analysis the two groups may not be independent as companies may shift between shooter and non-shooter categories. However, this is a feature of our analysis which we focus on in relation to H3.

two major groups of individuals within our sample.[11] To test **H3**, we replace our dummy variable indicating middleware use, with a continuous variable indicating the number of middleware components that the developer has previously used.[12]

We tested the robustness of the results using interactions, but chose to present stratified (split sample) results in order to ease interpretation. In our analysis we use LPM (OLS) regressions in order to make the interaction terms more easily interpretable. However, we tested the robustness of our results to logit regressions as well.

6. RESULTS

We begin by presenting our results for worker mobility in Table 3 (descriptive statistics shown in **Appendix A - Table A2)**. We begin by showing the dummies for the three main variables in Column 1, and the full set of interaction in Column 2. We find no significant effect with the exception of the three-way interaction, suggesting that prior to the diffusion of middleware, using middleware did not influence worker mobility, but following the diffusion of middleware workers were more likely to move between organizations. It is important to note that we include the dummy for middleware products, to ensure that we are looking at products where middleware was actually used. In Column 3, we include developer firm fixed effects, to capture unobserved differences between companies, as certain companies may be more likely to spur mobility (e.g., Ganco, 2013). As a robustness check, we expand the time window from 2005 to 2009. While this period did experience events that could have confounded our effects, such as the introduction of new hardware (PS3 and Xbox 360) which created

[11] We omitted workers that were not either programmers or creatives from the analysis. However, these groups represented a very substantial part of the entire game development team.

[12] In 90% of observations, this is identical to the data with the dummy variable. This variable captures differences between developers who had not worked with middleware previously and those working with their first middleware title. Additionally, this approach also indicates individuals who had worked with several middleware titles.

new opportunities for shooter games, as a robustness check we expand the time window to 2009 where middleware in shooter games expanded to approximately 80% of all titles. The results remain consistent suggesting that the diffusion of middleware led to greater mobility between companies. To aid in the interpretation of these interactions, we plot the marginal effects in Figure 2. While we observe a decline in both shooter and non-shooter games, for titles with middleware in the shooter category, the likelihood of leaving is 12% higher than for developers without middleware (44% greater than baseline). This result provides support for H1.

We explore the differences between creatives, which have skills which are more complementary to middleware, in comparison to programmers, which have skills that are in part likely to be replaced by middleware. We do this by repeating the analysis from above stratified by developer types. We first present the results for programmers Table 4, Columns 1 & 2, and then for creatives Table 4, Columns 3, & 4. While we do find a weak positive effect for programmers, we find a much stronger positive effect for creatives. To illustrate these results more clearly, we plot the results in Figure 3, where we show that while the diffusion does lead to greater mobility more generally, we find a weak positive effect for programmers 9% higher, while a stronger effect for creatives 30% higher. The difference between the two groups is significant. This provides evidence consistent with H2.

Finally, as a test of H3, we explore how individual mobility changes with middleware experience for creatives relative to programmers. We repeat the analysis by replacing our dummy variable that indicated the use of middleware, with a continuous variable that captures the number of middleware components that a developer has worked on. As part of our controls, we include the total number of projects that a developer has worked on. We present the regression results with the basic variables in Table 6, Column 1, and the interactions in Column 2. We find that more experience with middleware is associated with greater mobility. We also find that this is particularly true for creatives

(Column 4) while there is no significant effect for programmers (Column 3), in support of our H3.[13] We present marginal effects in Figure 4. While we find that for creatives with no middleware experience, there is an approximately 8% higher mobility for developers after the diffusion of middleware, for developers with ten projects of middleware experience this is approximately 200% greater (these values are plotted at a relatively high level of experience of 10 middleware projects to clearly plot the magnitude of these effects). These results are consistent with our theoretical arguments for how experience and the worker roles may shape developer mobility.

6.1 Robustness Checks

We perform a number of additional checks. First, we may be concerned that while our theoretical arguments are based on technological diffusion, our research design is based on comparing two periods, prior and following this diffusion. As an alternative and more direct measure of diffusion, we specify the diffusion based on the number of games using middleware components that are present in the marketplace **(Appendix A, Table A5)**. This is not our preferred specification as it is more difficult to directly interpret in a three-way interaction. We find results consistent with our main specifications. We also validated different definitions of "middleware components" as only a small subset of all middleware tools became widely diffused. We found that our results held only with middleware components that became widely diffused, consistent with our theoretical arguments. Additionally, if our main arguments are consistent with broader patterns, than we would expect to see fewer creatives leaving the shooter category, particularly following the diffusion of middleware. We find evidence consistent with these arguments **(Appendix A, Table A3 & Figure A1)**. As a further check, we consider whether workers are leaving the industry more generally from the shooter category

[13] We present split sample results to ease interpretability. However, we tested the significance in a single model with an indicator for the creatives and the full set of interactions. Results remained consistent.

as a consequence of the diffusion of middleware, but find no evidence of this relationship. **(Appendix A, Table A4).** We provide a summary of the different robustness checks in Table 7.

7. DISCUSSION AND CONCLUSION

In this paper we study how the diffusion of standardized tools shapes the mobility of individual workers between companies. While worker mobility has been studied as an important strategic issue (Byun et al., 2018; Bidwell & Mollick, 2015; Bidwell et al., 2015; Campbell et al., 2012), there has been less work in terms of the impact of technologies and technological change on worker mobility. Here, we focus on the fact that while the diffusion of technologies may provide benefits for companies, it leads workers to become more exposed to general tools and technologies, making their skills and experience less firm specific, and more general. This reduces the labor market frictions that may prevent workers from moving between companies, leading to greater mobility (Mahoney and Qian, 2013; Mawdsley and Somaya, 2016). This also varies with worker experience, as workers with skills which are complementary to this technological shift, and workers which have considerable experience with this technology, are more likely to gain an increase in the value of their skills and move between companies.

While technological change has always been an important factor in shaping organizations, the increasingly rapid pace of technological change has led to calls for a greater understanding of how technology shapes organizations. As motivated earlier, knowledge workers are often critical to organizations, yet, studies looking at the impact of technology on organizations and their workers have typically focused on lower skilled workers, with a small number of notable exceptions (Greenwood, et al., 2019; Horton & Tambe, 2019). The results of this paper suggest that these technological changes, specifically the diffusion of a standardized set of tools, may considerably influence the mobility decisions of knowledge workers. On the one hand, it can increase the substitutability among certain workers, creating a potential benefit for companies. However, on the other hand, this may enhance the relative importance of other workers, particularly those with complementary skills. This might indicate an un-intended consequence of the diffusion of such tools.

These results inform our understanding of how the diffusion of tools shapes worker mobility, and in turn the career progression of individuals, but also the worker composition of many organizations. While this contributes to our broader understanding of these issues (Faraj et al., 2011; Yoo et al., 2012), it also relates to technologies such as Artificial Intelligence or Blockchain, which are expected to become increasingly widespread in a range of industrial settings (Furman and Seamans, 2019). As these technologies diffuse, and more importantly tools around these technologies diffuse (e.g. Tensorflow and other AI software tools, IBM Blockchain solution for tracking product provenance), they will undoubtedly shape organizations in a wide range of settings. The results from the present study suggest that the diffusion of these technologies may end up shaping workers and organizations in unexpected ways, as it on the one hand automates tasks of some workers, but increases the mobility of others.

7.2 Implications for Practice

The ability for companies to retain and control various assets, including human capital, is an important determinant for their success (Barney, 1991; Campbell et al., 2012). While there may be benefits to working on a set of diffused and well-known technologies, the reliance on a common set of technologies can make it difficult for companies to differentiate themselves from competitors (Klepper, 1996; Ranganathan et al., 2018). Therefore, this can force companies to rely more on their other assets, including their human capital assets. Given that those assets which are complementary to the displacing technology may be most valuable (Agrawal, et al., 2018), the ability of companies to differentiate themselves may depend on being able to retain those workers. Yet, at the same time, the present result suggests that these technological changes may lead workers to shift between companies, which could potentially threaten the benefits from using these technologies. As we consider the growth of technologies such as AI and Blockchain, while they may bring considerable gains for companies, it may prove harder to retain the workers which complement these technologies, making it challenging for companies to fully benefit from these technologies. While there are many deeper issues to be understood relating how organizations can orchestrate a balance of workers and technologies, the present results suggest that the diffusion of technologies, particularly for highly skilled workers, may lead to greater mobility between companies.

7.3 Limitations and Conclusion

While the theoretical arguments we develop apply broadly to a wide range of technologies, our empirical context is focused on a setting where the resulting products are digital and the tools studied pertain to software components and applications. While these results may have insights for the wide range of digital settings which are growing in prominence, additional work may be needed to understand to what extent these results may apply to non-digital settings. However, in general these results do suggest that technological change and the diffusion of tools can greatly influence the mobility of individual workers which has important implications for organizations.

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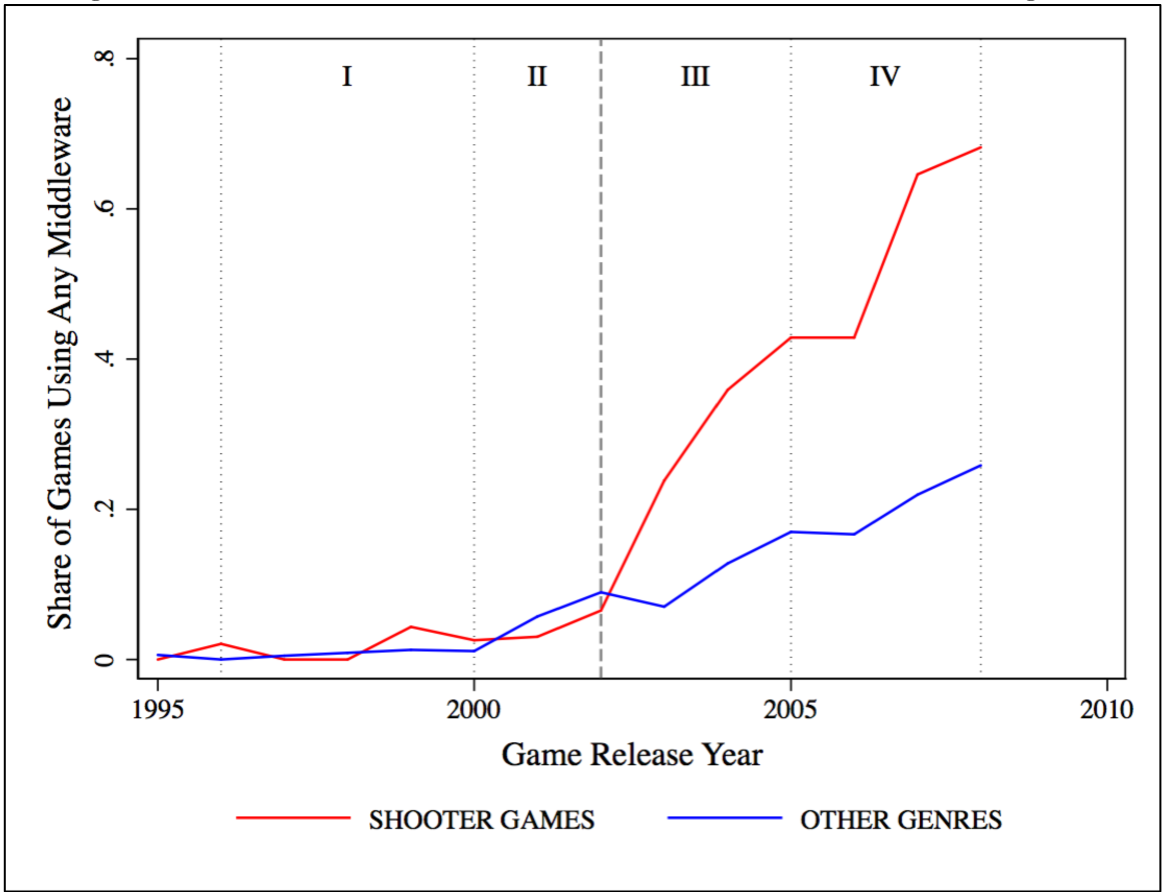
TABLES AND FIGURES

Figure 1. Share of Middleware Based Titles in Shooter and Non-Shooter Categories



Note: Middleware components defined as either "Game Engines", "Physics Engines", "3D Engines" and "Graphics Engines". Increase in middleware use within SHOOTER Games occurs after 2002, when the Unreal Engine, becomes introduced and used by various 3rd Parties in the Video Game Sector.

Table 1. Overview of Periods in Research Design

Period	**I. Early Console**	**II. Pre-Middleware**	**III. Middleware Growth**	**IV. Changes in SHOOTER Games**
Time Window	*1995 - 1998*	*1999 - 2002*	*2003 - 2005*	*2006 - 2008*
Summary	Prior to the launch of Xbox and PS 2.	Period when Xbox and PS2 grew in dominance, before middleware was introduced.	Period when Unreal Engine was released followed by other middleware in Shooter games where early middleware was most easily adapted	Period when new hardware was released, shifting focus to a small number of very large projects.
Main Sample	Y	Y	Y	
Robustness Sample	Y	Y	Y	Y

Table 2. Summary of Different Comparison Groups

	i. Summary of Middleware Technology Diffusion	
	NON – SHOOTER	**SHOOTER**
Pre 2002	Middleware components used by very small numbers of developers. These components are often proprietary, or specialized.	
Post 2002	Middleware component diffuse very slowly, only becoming moderately diffused by 2008, due to the technology being suited for SHOOTER applications.	Middleware components rapidly diffuse starting with Unreal Engine, becoming used by almost 50% of titles by 2005, and 80% of titles by 2008.

	ii. Overview of Project / Developer Characteristics	
	NO MIDDLEWARE	**MIDDLEWARE**
Projects (H1, H2)	Require more specialized skills and knowledge.	Require More general, easily transferable skills (easier to hire externally)
Experience (H3)	Experience more "firm specific" as prior work involved using firm specific tools, instead of more general middleware, used by others.	Less firm specific experience that may be transferred, as experience is based on tools which are used by many companies.

Figure 2. **[Marginal Effects for Baseline Mobility Results]**
Change in Worker Mobility Within Shooter and Non-Shooter Categories
Following diffusion of middleware components.

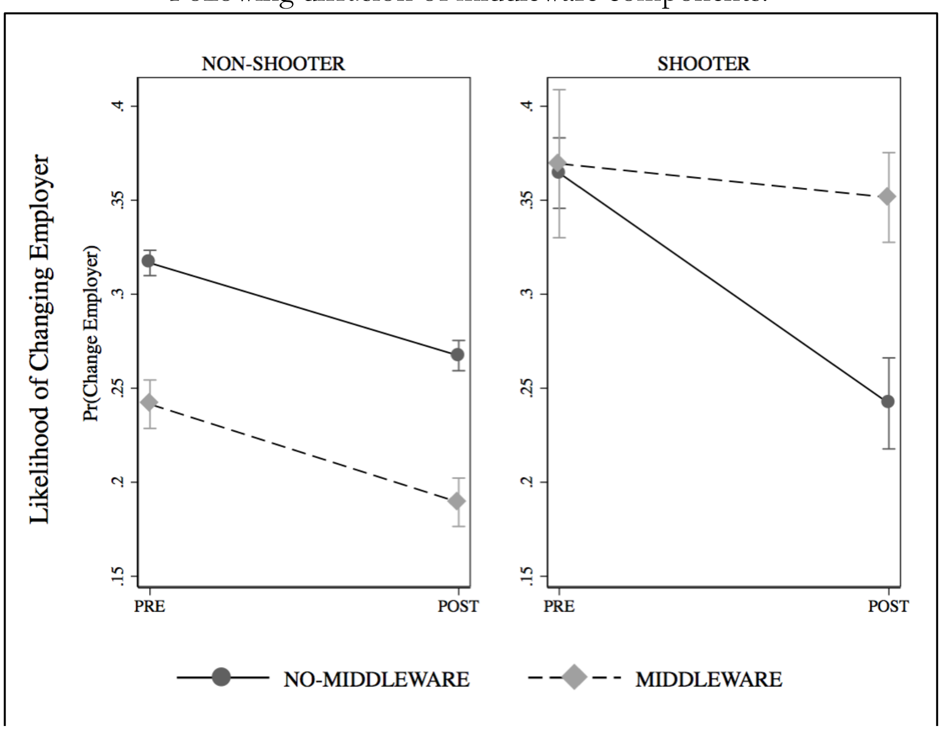


Figure 3. **[Marginal Effects for Position Type Results]**
Change in Worker Mobility Based on Role Type [Creatives vs. Programmers]

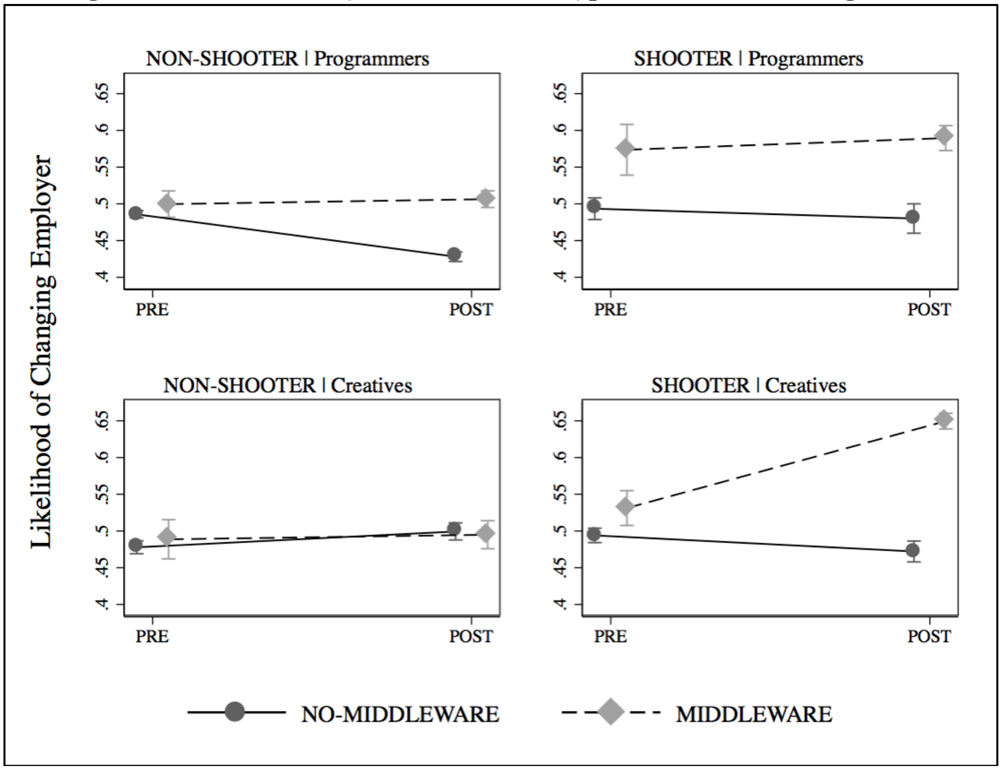


Figure 4. **[Marginal Effects for Mobility Results by Experience]**
Change in Worker Mobility based on Developer Experience

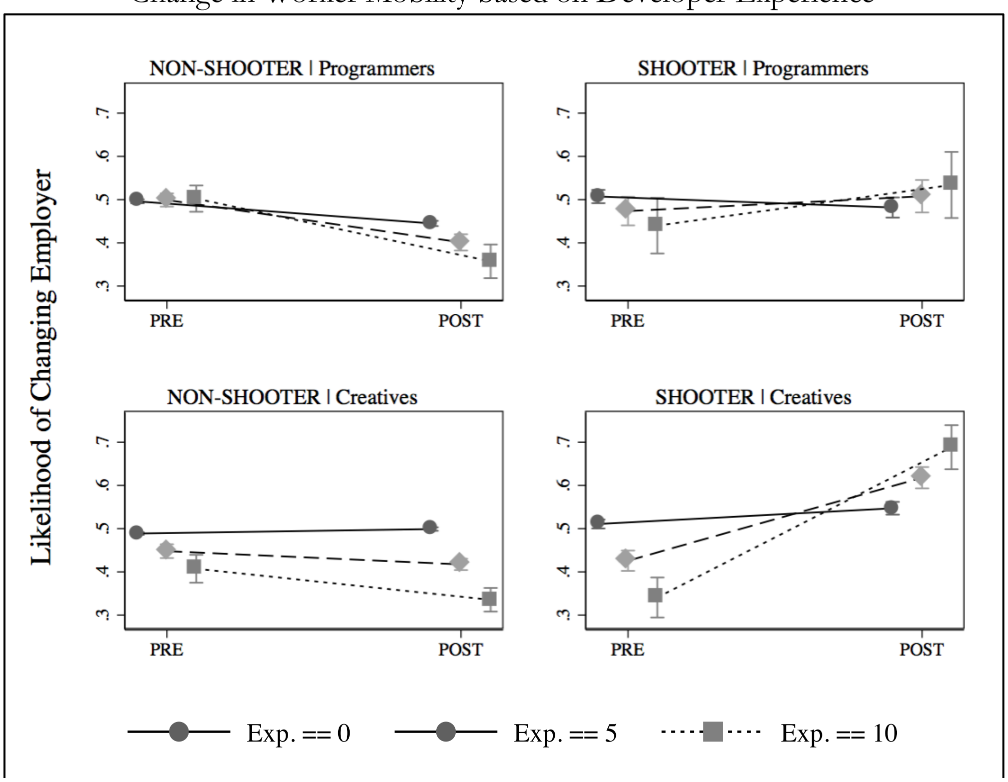


Table 3. Baseline Regression Results for Individual Mobility Between Employers
Outcome: *Pr(Change in Employer = 1)*. **Unit of Observation:** *Worker - Project*

	(1)	(2)	(3)	(4)
SHOOTER	0.043***	0.009	0.009	0.004
	(0.007)	(0.010)	(0.010)	(0.011)
Post Middleware	0.008	-0.000	-0.000	-0.032**
	(0.007)	(0.009)	(0.009)	(0.012)
Middleware	0.035***	0.013	0.013	0.027
	(0.007)	(0.012)	(0.012)	(0.014)
Post Middleware x Middleware		0.008	0.008	-0.004
		(0.014)	(0.014)	(0.014)
Post Middleware x SHOOTER		-0.018	-0.018	-0.011
		(0.017)	(0.017)	(0.016)
SHOOTER x Middleware		0.038	0.038	-0.011
		(0.028)	(0.028)	(0.033)
SHOOTER x Middleware		0.101**	0.101**	0.106**
x Post Middleware		(0.033)	(0.033)	(0.036)
Experience	0.001**	0.001**	0.001**	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Game Sales	-0.005	-0.005	-0.005	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Project Size (Employees)	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Middleware Exp.	-0.004	-0.003	-0.003	-0.004**
	(0.002)	(0.002)	(0.002)	(0.001)
Constant	-16.318***	0.610***	0.610***	0.683***
	(3.437)	(0.063)	(0.063)	(0.058)
Developer FE			Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes
Ethnicity & Gender Dummies	Yes	Yes	Yes	Yes
N	74338	74338	74338	110581
R^2	0.010	0.013	0.013	0.190
F	20.028	20.957	20.957	17.343
	(0.000)	(0.000)	(0.000)	(0.000)

** p<0.05, ** p<0.01, *** p < 0.001 (Robust Standard Errors in parentheses)*

Table 4. Regression Results for Individual Mobility Between Employers Conditional on Worker Type
Outcome: *Pr(Change in Employer = 1)*. **Unit of Observation:** *Worker - Project*

	(1)	(2)	(3)	(4)
	Programmers		*Creatives*	
SHOOTER	0.013	-0.000	0.039***	0.012
	(0.016)	(0.020)	(0.011)	(0.013)
Post Middleware	-0.058**	-0.065***	-0.014	-0.004
	(0.018)	(0.019)	(0.011)	(0.012)
Middleware	-0.008	-0.042	0.019	0.043*
	(0.016)	(0.026)	(0.011)	(0.017)
Post Middleware x Middleware		0.023		-0.087***
		(0.029)		(0.019)
Post Middleware x SHOOTER		-0.041		-0.069**
		(0.042)		(0.026)
SHOOTER x Middleware		-0.003		-0.060
		(0.062)		(0.043)
SHOOTER x Middleware		0.149*		0.341***
x Post Middleware		(0.075)		(0.051)
Experience	0.003**	0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Total Game Sales (USD)	0.003	0.004	0.008	0.011
	(0.009)	(0.009)	(0.006)	(0.006)
Project Size (Employees)	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Middleware Exp.	-0.002	-0.002	-0.012***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.382**	0.366**	0.359***	0.317***
	(0.136)	(0.136)	(0.089)	(0.089)
Developer FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes
Ethnicity & Gender Dummies	Yes	Yes	Yes	Yes
N	21092	21092	53246	53246
R^2	0.241	0.242	0.198	0.200
F	5.114	5.053	7.374	9.322
	(0.000)	(0.000)	(0.000)	(0.000)

** p<0.05, ** p<0.01, *** p < 0.001 (Robust Standard Errors in parentheses)*

Table 6. Regression Results for Individual Mobility Between Employers Conditional on Middleware Experience
Outcome: *Pr(Change in Employer = 1)*. **Unit of Observation:** *Worker - Project*

	(1)	(2)	(3)	(4)
	Baseline Results		*Programmers*	*Creatives*
SHOOTER	0.030***	0.010	-0.001	0.013
	(0.009)	(0.011)	(0.019)	(0.013)
Post Middleware	-0.026**	-0.027**	-0.058**	-0.017
	(0.010)	(0.010)	(0.018)	(0.012)
Middleware Exp.	-0.006**	-0.001	0.001	-0.008*
	(0.002)	(0.003)	(0.004)	(0.004)
Post Middleware x Middleware Exp.		-0.012***	-0.009	-0.008
		(0.004)	(0.006)	(0.005)
Post Middleware x SHOOTER		0.036*	0.029	0.048*
		(0.018)	(0.033)	(0.021)
SHOOTER x Middleware Exp.		-0.011	-0.007	-0.009
		(0.006)	(0.008)	(0.007)
SHOOTER x Middleware Exp.		0.037***	0.021	0.039***
x Post Middleware		(0.008)	(0.014)	(0.010)
Job Type [Creative / Programmer]	-0.003	-0.003		
	(0.004)	(0.004)		
Experience	0.001**	0.001**	0.003**	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Total Game Sales	0.008	0.009	0.003	0.010
	(0.005)	(0.005)	(0.009)	(0.006)
Project Size (Employees)	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-16.318***	0.610***	0.610***	0.683***
	(3.437)	(0.063)	(0.063)	(0.058)
Developer FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes
Ethnicity & Gender Dummies	Yes	Yes	Yes	Yes
N	74338	74338	21092	53246
R^2	0.193	0.194	0.242	0.199
F	9.348	9.550	4.947	7.731
	(0.000)	(0.000)	(0.000)	(0.000)

** p<0.05, ** p<0.01, *** p < 0.001 (Robust Standard Errors in parentheses)*

Table 7. Summary of Robustness Checks

Concern	Solution	Outcome
Binary outcome variable may influence significance and hypothesis tests (OLS primarily used in paper).	Analysis repeated with logistic regression and predicted values plotted to ensure results remained consistent.	Results remained consistent. OLS still preferred because the coefficients and interactions can be more readily understood.
Diffusion measured indirectly comparing periods before and after diffusion of middleware. using Post 2002.	Constructed variable to measure the diffusion of middleware tools based on a count of the number of middleware components currently available [N. Middleware Components]	Results remain consistent (Table A5).
Length of Time Window [Extensive diffusion does not happen until 2006 - 2008]	Repeat analysis with extended time window.	Results remain consistent (Table 3, Column 4). While we only show this result, we checked to ensure results were robust in other specifications.
Workers leaving industry following middleware diffusion. This "Exodus" could have influenced mobility results	Estimate whether workers were more likely to leave following the diffusion of middleware.	Results suggest workers were not leaving the industry following the diffusion of middleware, more than the baseline rate.
Workers shifting between categories (niches) following middleware diffusion.	Estimate whether mobility between categories changed following the diffusion of middleware.	Results suggest that specifically creatives were more likely to remain in the SHOOTER category, while Programmers were no more likely to shift then the baseline. (Table A3, Figure A1). This suggests that it is not biasing our results, and the results are consistent with our theoretical arguments.

APPENDIX A. SUPPLEMENTARY TABLES

Table A1. Variable Definitions

VARIABLE	DEFINITION
Measures of Individual Mobility	
Change Companies	Indicator of whether a worker is employed by a different company (developer) in period t, in comparison to period t-1.
Change Market Niche	Indicator of whether a worker is working in a project within a different market niche (e.g. SHOOTER games) in period t, in comparison to period t-1.
Leave Industry	Indicator of whether a developer's position is the last one before they leave the industry.
Measures of Middleware Diffusion	
Post Middleware	Indicator for periods after 2002, when Middleware Components became increasingly diffused.
SHOOTER	Indicator for "SHOOTER" market niche, which was where early middleware components were first introduced, and where they most widely diffused.
MIDDLEWARE	Indicator for whether a particular title uses middleware components.
Important Covariates	
Middleware Experience	Number of Projects which used middleware that the worker has been involved with.
Role [Programmer / Creative]	Indicator for whether a developer is a Creative [Works with Design, Art, Graphics, Writing, Audio or Video Engineering] or Programmer [Works with Programming or Engineering]
Control Variables	
Year FE	Indicator variables for each year in which the titles were released.
Platform FE	Indicator variables for the platform that a particular title has been released on.
Developer FE	Indicator variables for the company that the developer has worked for (previously worked for). [Proxy for various factors related to company prestige, characteristics, retention policies, etc.]
Job Experience	Number of Projects that the particular worker has previously worked on.
Total Game Sales	Total USD Sales of game title following release (Proxy for various factors related to game popularity, prestige or other factors).
Middleware Experience	Number of projects that the developer has previously worked on that used middleware components [focused on known components used across different titles.]
Gender & Ethnicity	Gender and Ethnicity inferred using classification algorithm based on US Census data, which predicts names with certain reliability.
Company Tenure	Number of previous projects with previous employer

Table A2. Descriptive Statistics

	Mean	**Std. Dev.**	**Min**	**Max**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
(1) *Change Company*	0.48	0.50	0.00	1.00	1.00													
(2) *Change Niche*	0.53	0.50	0.00	1.00	0.35	1.00												
(3) *Leave Industry*	0.28	0.45	0.00	1.00	0.02	-0.11	1.00											
(4) *Post Middleware*	0.37	0.48	0.00	1.00	0.06	0.01	-0.01	1.00										
(5) *Shooter*	0.09	0.29	0.00	1.00	0.04	0.06	-0.01	0.06	1.00									
(6) *Middleware*	0.15	0.35	0.00	1.00	0.03	0.01	-0.02	0.27	0.21	1.00								
(7) *Number of Middleware Titles*	27.01	19.99	0.00	64.00	0.03	-0.02	-0.01	0.69	-0.29	0.22	1.00							
(8) *Middleware Experience*	0.35	1.14	0.00	38.00	0.01	-0.02	-0.06	0.17	0.12	0.56	0.14	1.00						
(9) *Role Creative*	0.73	0.44	0.00	1.00	0.01	-0.05	0.06	-0.01	-0.01	-0.01	-0.01	-0.02	1.00					
(10) *Job Experience*	3.48	3.87	1.00	80.00	0.01	-0.03	-0.19	0.04	0.00	0.01	0.05	0.31	-0.03	1.00				
(11) *Company Tenure*	1.93	1.99	1.00	52.00	-0.46	-0.14	-0.14	-0.01	-0.03	-0.02	0.01	0.21	-0.03	0.58	1.00			
(12) *Total Game Sales (USD) - logged*	16.57	1.08	1.73	8.16	0.01	-0.03	-0.03	0.47	-0.06	0.22	0.42	0.15	-0.03	0.07	0.04	1.00		
(13) *N Platforms for Title*	1.68	0.93	1.00	9.00	0.01	-0.02	-0.07	0.20	0.00	0.24	0.23	0.14	-0.08	0.05	0.01	0.44	1.00	
(14) *Project Size*	117.73	103.83	1.00	717.00	0.05	-0.03	-0.01	0.33	0.09	0.32	0.28	0.19	0.02	-0.01	-0.04	0.28	0.38	1.00

Sample based on (full sample) data between 1995 and 2008.

Table A3. Regression Results for Individual Mobility Between Market Niches
Outcome Variable: *Pr(Change Market Niche = 1),* **Unit of Observation:** *Worker - Project*

	(1)	(2)	(3)	(4)
	Baseline Results		*Programmers*	*Creatives*
SHOOTER	0.633***	0.664***	0.645***	0.677***
	(0.010)	(0.014)	(0.025)	(0.017)
Post Middleware	-0.017	-0.011	0.001	-0.020*
	(0.009)	(0.009)	(0.019)	(0.010)
Post Middleware x SHOOTER		-0.059**	0.023	-0.082***
		(0.020)	(0.038)	(0.025)
Job Type [Creative / Programmer]	-0.003	-0.003		
	(0.003)	(0.003)		
Experience	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Total Game Sales	-0.025***	-0.025***	-0.043***	-0.020***
	(0.005)	(0.005)	(0.010)	(0.006)
Project Size (Employees)	0.000***	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Middleware Exp.	-0.004*	-0.004*	-0.004	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	0.487***	0.487***	0.773***	0.408***
	(0.080)	(0.080)	(0.165)	(0.094)
Developer FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes
Ethnicity & Gender Dummies	Yes	Yes	Yes	Yes
N	36203	36203	10011	26192
R^2	0.532	0.532	0.584	0.539
F	103.080	104.213	35.274	75.504
	0.000	0.000	0.000	0.000

** p<0.05, ** p<0.01, *** p < 0.001 (Robust Standard Errors in parentheses)*

Outcome variable indicates whether worker left the niche (SHOOTER or NON-SHOOTER) on their subsequent project. Results indicate that workers, and specifically creatives, within the shooter category, were more likely to remain in the SHOOTER niche after middleware diffused. This is consistent with the theoretical arguments regarding the diffusion of these tools and how it impacts worker human capital.
Marginal effects to aid interpretation shown in Figure A1.

Figure A1. **[Marginal Effects for Industry Change – Table A3, Columns 3&4]**
Change in Niche Based on Developer Type, and
Whether Previous Position was in SHOOTER or any other niche

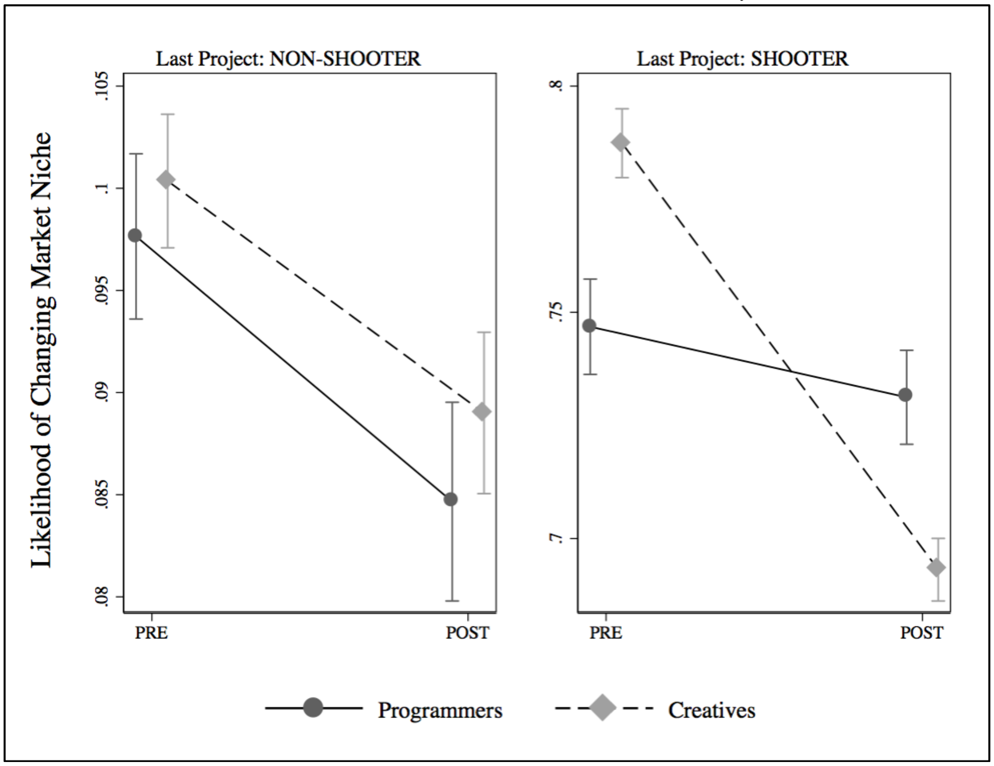


Table A4. Baseline Regression Results for Individuals Leaving Industry

Outcome Variable: *Pr(Leaving Industry = 1),* **Unit of Observation:** *Worker - Project*

	(1)	(2)	(3)	(4)
	Baseline Results		*Programmers*	*Creatives*
SHOOTER	0.014*	0.009	-0.003	0.009
	(0.006)	(0.007)	(0.013)	(0.009)
Post Middleware	0.083***	0.081***	0.070***	0.089***
	(0.007)	(0.007)	(0.013)	(0.008)
Post Middleware x SHOOTER		0.016	0.016	0.020
		(0.011)	(0.020)	(0.013)
Job Type [Creative / Programmer]	-0.018***	-0.018***		
	(0.003)	(0.003)		
Experience	-0.018***	-0.018***	-0.012***	-0.020***
	(0.000)	(0.000)	(0.001)	(0.000)
Total Game Sales	0.006	0.006*	0.010	0.006
	(0.003)	(0.003)	(0.006)	(0.004)
Project Size (Employees)	0.000***	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Middleware Exp.	-0.002	-0.002	0.003	-0.007**
	(0.002)	(0.002)	(0.003)	(0.002)
Constant	0.307***	0.306***	0.196*	0.315***
	(0.049)	(0.049)	(0.090)	(0.059)
Developer FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes
Ethnicity & Gender Dummies	Yes	Yes	Yes	Yes
N	116397	116397	31432	84965
R^2	0.125	0.125	0.132	0.138
F	109.335	106.908	20.511	87.828
	0.000	0.000	0.000	0.000

** p<0.05, ** p<0.01, *** p < 0.001 (Robust Standard Errors in parentheses)*

Table A5. Regression Results for Individual Mobility Between Employers Conditional on Experience using alternative diffusion variable (i.e. N Middleware Titles)

Outcome: *Pr(Change in Employer = 1)*. **Unit of Observation:** *Worker - Project*

	(1)	(2)	(3)	(3)	(4)
		Baseline Results		*Programmers*	*Creatives*
SHOOTER	-0.055***	-0.038**	-0.011	-0.078**	0.018
	(0.012)	(0.014)	(0.016)	(0.029)	(0.020)
N. Middleware Titles	-0.004***	-0.004***	-0.003***	-0.006***	-0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Middleware	0.029***	-0.032	0.006	-0.074	0.036
	(0.006)	(0.018)	(0.022)	(0.040)	(0.026)
N. Middleware Titles x Middleware		0.001**	-0.001	0.001	-0.001**
		(0.000)	(0.000)	(0.001)	(0.001)
N. Middleware Titles x SHOOTER		-0.006***	-0.010***	-0.007	-0.011***
		(0.002)	(0.002)	(0.004)	(0.002)
SHOOTER x Middleware		0.059	-0.039	0.001	-0.044
		(0.032)	(0.041)	(0.073)	(0.051)
SHOOTER x Middleware x N. Middleware Titles		0.006**	0.014***	0.007	0.017***
		(0.002)	(0.003)	(0.005)	(0.004)
Job Type [Creative / Programmer]	-0.016***	-0.016***	-0.003		
	(0.004)	(0.004)	(0.004)		
Experience	0.001***	0.001***	0.001**	0.002*	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Total Game Sales	0.001***	0.001***	0.001**	0.002*	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Project Size (Employees)	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.867***	0.867***	0.542***	0.734***	0.464***
	(0.071)	(0.078)	(0.091)	(0.170)	(0.109)
Platform, Year, Ethnicity & Gender FE	Yes	Yes	Yes	Yes	Yes
Developer FE			Yes	Yes	Yes
N	74338	74338	74338	21101	53224
R^2	0.13	0.014	0.196	0.241	0.201
F	9.382	22.837	10.855	5.240	8.644
	(0.000)	0.000	0.000	0.000	0.000

* *p<0.05, ** p<0.01, *** p < 0.001 (Robust Standard Errors in parentheses)*