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Protecting their digital assets: The use of formal & informal appropriability strategies by App developers[☆]

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ABSTRACT

Innovators and entrepreneurs developing products and competing “on top” of digital platforms face different conditions than do those in more traditional industries. In this paper, we explore how this affects appropriability strategies in novel data on mobile app developers’ appropriability strategies. We find that the many smallest developers in the “long tail”— the vast majority of all developers – do in fact take actions to capture value and to protect their intellectual property, but do so only through informal mechanisms. By contrast, larger developers exploit a combination of both informal mechanisms and formal intellectual property rights, using copyright, patents, and trademarks. Several strategies particular to digital platforms are also documented. We link this pattern of different strategies pursued by different competitor types to the structural features of digital competition.

1. Introduction

A central question in the study of innovation is appropriability, that is, how innovators are able to protect and profit from their innovations so that they have an incentive to undertake innovation in the first place (Arrow, 1962; Levin et al., 1987; Laursen and Salter, 2014; Teece, 1986). Over the past decade, the emergence of digital platforms has given rise to a new mode of production (Gawer and Cusumano, 2002; Tiwana, 2004; Parker et al., 2016), allowing smaller firms to create complementary innovations on top of platforms to bring them to market. While the importance of third-party developers appropriating value has been established (Huang et al., 2012; Parker and Alstyne, 2017; Gawer and Henderson, 2007), little of the research on appropriability mechanisms and strategies (Cohen et al., 2000; Levin et al., 1987; Hall and Ziedonis, 2001) has yet examined touched on the strategies of these innovators working on digital platforms. In this paper, we seek to provide more insights into this under-studied question, and particularly how the smallest developers on digital platforms, protect and appropriate value from their innovations.

The value of digital platforms depends on the availability of complements (Parker and Alstyne, 2005; Rochet and Tirole, 2006). For instance, the value of computer operating systems depends on the availability of complementary third-party software. As a result, platform owners have tried to increase ease of access and lower the costs of developing for their platforms, to allow even small firms or individuals to do so, and for a “long tail”of developers to join, including hobbyists and amateurs. While these small-scale innovations may individually account for a tiny share of revenue, collectively the long tail can sometimes represent a considerable share of economic activity. Take, for example, that most developers on both the Unity asset store and the Salesforce app market are small 3rd-party developers generating billions of dollars in revenue. For many of these innovators, the ability to appropriate value and profit may be important to motivating them to join the platform in the first place (Huang et al., 2012; Parker and Alstyne, 2017; Gawer and Henderson, 2007). Little is yet known about how such small developers protect their innovations, including whether

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they rely on intellectual property rights (IPR) to protect their innovations the same way that larger firms typically choose to do. For instance, there has been little exploration of how developers might protect their innovation in contexts where the cost of getting a patent, itself, might often exceed the expected revenues from selling the product, or where it is uncertain whether property rights are practically enforceable (Graham et al., 2009).

The question of appropriability is critical to the study of innovation and innovation policy; it helps policymakers to create conditions to incentivize innovation (Arrow, 1962). In this context, the question of how third-party developers appropriate value is perhaps even more important, because the success of the platform depends on the ability of the platform regulator to attract complementers to create third-party products (Boudreau, 2010; Gawer and Cusumano, 2014; Parker and Alstyne, 2005). As Gawer and Cusumano (2014) noted, “platform leaders tend to successfully stimulate a certain kind of externally developed innovation (that would complement the platform).”Earlier studies have provided insights into how firms appropriate value from their innovations (Levin et al., 1987; Cohen et al., 2000; Laursen et al., 2014; Hall and Ziedonis, 2001; Graham et al., 2009; Hall and Sena, 2017; Arundel, 2001; Huang et al., 2012) and the broad strategies that firms (can) use to protect their assets resulting from their innovation (Teece, 1986). Out of this interest has emerged a body of empirical studies documenting appropriability strategies by large firms, predominantly in manufacturing industries (Cohen et al., 2000; Levin et al., 1987). More recently, studies have looked at forms of appropriability in traditional software development (Cockburn et al., 2011; Bessen and Hunt, 2007; Hall and Ziedonis, 2010), but these still generally focuses on larger firms. The literature regarding appropriability by smaller innovators has focused often on software developers that may freely reveal their innovations to derive indirect monetary benefits (Harhoff et al., 2003). However, many small developers may want to profit from their innovations, particularly on digital platforms. None of these earlier studies have considered how smaller innovators that seek to profit from their innovations by selling or commercializing their products will choose to appropriate value from their innovations.

To make progress in understanding how innovators protect their innovations on digital platforms, we study appropriability strategies of innovators on the Apple App Store—the largest and economically most important case of competing innovators working on a digital platforms, today. Beyond its sheer economic magnitude, the Apple App Store presents a useful case to study in that its products cover a wide range of particular digital product types (e.g., productivity, gaming, education, and finance apps, and many more). Studying the Apple App Store also permits us to study a wide cross-section of types of innovators, including both large and small developers, including independent developers, micro-enterprises, and part-time developers. This is also a context to observe strategies in an increasingly typical cases where the platform owner itself, Apple, takes actions to support enforceability of US patent, copyright, and trademark laws.

In this study, we begin by framing the use of appropriability strategies along the lines as has been identified in earlier studies (i.e., patents, copyrights, trademarks, lead time, and rapid innovation). We are guided, in particular, by the framework established in Yale and later Carnegie Mellon surveys (Cohen et al., 2000; Levin et al., 1987) for our data collection on the use of formal and informal mechanisms. Apart from the use of appropriability mechanisms, our global app developer survey also collected a range of information on developer attributes, strategies, perceptions of competition, and appropriability concerns. We match our survey data to an observational data set covering the full population of app developers, in which we observe all titles and versions developed by all developers, across all distinct categories or genres of apps (e.g., games, travel, references). We use the observational data to reweigh our survey responses to ensure representativeness of the survey sample and an accurate estimation of population-level patterns. (Fortunately, the survey responses are themselves highly representative of the population, and reweighing to reflect the population does not substantially alter results.)

We find that appropriability strategies used by developers on the Apple App Store cluster onto several combinations of approaches. Of those firms that attempt to protect their innovations (70.59% of firms), the majority use either only informal strategies (36.76%) or a combination of formal and informal strategies (24.12%). Only a small proportion of all firms (9.71%) utilize only formal protections. A considerable share of developers do not report using any form of appropriability strategy (29.5%),

To identify key correlates with these clusters of appropriability strategies, we use a variable selection model commonly used in machine learning applications that has been adapted to econometric applications (Double LASSO by Belloni et al., 2013, 2014). A main finding is that a first-order distinction exists between strategies used by large and small developers. Our analysis shows that informal IPR protections are used by very small firms and part-time developers, while larger firms use formal IPR protections alongside informal strategies. The findings are robust to including in the analysis controls for developer motivations, revenue models, sources of innovation, and products characteristics.

Our study most directly contributes to the extensive literature on appropriability strategies (Teece, 1986; Cohen et al., 2000; Levin et al., 1987), where here we take an early step toward understanding these issues in the increasingly important context of digital platforms, where structural conditions fundamentally differ (Greenstein et al., 2013; Goldfarb et al., 2015; Yoo et al., 2010; Nambisan et al., 2017) from those in previously-studied manufacturing and bricks-and-mortar industries, reviewed herein. For instance, this includes a relative ease of developing innovations “on top” of platforms, and relative ease of copying or replicating digital innovations.

This paper also contributes to research on platforms that has considered how third-party developers can protect themselves from having the value of their innovations expropriated. Whereas the past literature has tended to study the possibility of the platform owner engage in profit-squeezing or vertical integration into a given complement (Gawer and Henderson, 2007; Parker and Alstyne, 2017; Huang et al., 2012; Foerderer et al., 2018; Zhu and Liu, 2018; Boudreau, 2010), whereas here we focus on the threat of peer developers.

2. Literature review

As a backdrop for our study of appropriability on digital platforms, we provide an overview of appropriability as it relates to the literature on the economics of innovation.

The patent's role as a legal/formal protection mechanism has been prominent in studies of appropriability. The purpose of patent rights is to provide innovators with exclusive rights to use an innovation in exchange for disclosing the inner workings of the technology. Existing studies have found that innovators report using a wide range of strategies in addition to or instead of patents to limit competition and appropriate value from their innovations, including other formal property rights (e.g., copyrights and trademarks) and informal strategies, such as first-mover advantages and design complexity (Levin et al., 1987; Cohen et al., 2000). In some cases, firms may rely on proprietary complementary assets in manufacturing, distribution, and marketing, sales, and service (Teece, 1986). At times, innovators choose to forgo patent protection to avoid disclosing the required inner workings of their innovation (Png, 2017; Arundel, 2001). In other cases, firms use a combination of patents to protect certain elements of their innovation and secrecy to protect other elements (Levin et al., 1987). The decision of whether firms will use patents, combined with or instead of some other form of protection, depends largely on the effectiveness of the IPR regime for that particular innovation, the characteristics of the focal firm, and the cost of deploying the mechanism (Teece, 1986; Graham et al., 2009).

2.1. Effectiveness of IPR and appropriability strategies

An important feature of whether firms protect through patents or alternative strategies depends largely on the effectiveness of patent protection (Teece, 1986). Prior studies have attempted to determine this effectiveness in a variety of ways. Several papers have explored how the introduction of patents or trade secrets protection influences innovative activity (Moser, 2005, 2013; Png, 2017). These studies have found that patent protection leads to more innovation, suggesting that patents are effective at protecting innovation. Similar approaches have been used to test the effectiveness of copyrights and trademarks (Moser, 2013; Png, 2017). Other studies have investigated patent filing and renewal decisions and used this to infer whether patent rights are an effective means of appropriating value and what this means for innovation (Hall and Ziedonis, 2001; Bessen and Hunt, 2007; Lanjouw and Schankerman, 2001). Several studies have focused on the relationship between holding patents and firm performance in a competitive market. These studies find that patents are an effective means of appropriating value from innovation (Cockburn and MacGarvie, 2011; Cockburn and Griliches, 1987). Some studies have attempted to quantify the "patent premium" or boost to revenues that results from innovators using patents or copyrights to protect their innovation (Arora et al., 2008). Other studies have surveyed companies, asking them whether they use formal IPR and whether they perceive IPR to be an effective means of appropriating value (Levin et al., 1987; Cohen et al., 2000).

The consensus from this literature is that patents can provide an effective means of appropriating value from an innovation. This holds true for software industries, where patents may not necessarily be as widely used as in other settings but have still been found to be effective at protecting innovations and in strategic maneuvering (Bessen and Hunt, 2007). Interestingly, the incentives to use patents have been found to be lower for small firms (See Graham et al., 2009). It is also clear that patents are not the only means through which firms are able to appropriate returns. In many cases, firms use a variety of other strategies in addition to patents to protect their innovation, and they often do so through a combination of formal and informal means (Cohen et al., 2000). For instance, patents are often a natural complement to early entry or lead-time advantages (Graham et al., 2009). Existing studies have not empirically explored how innovators might combine different appropriability strategies or how those combinations vary by industry or firm characteristics (James et al., 2013).

Innovators may combine formal and informal appropriability strategies. For instance, firms that have lead-time advantages from entering early may want to protect those advantages by patenting their technology. Alternatively, a firm may patent part of its technology while protecting another part through informal means (Levin et al., 1987) or may delay it's entry on account of the time it takes to acquire a patent (Gans and Stern, 2017). While there is an expectation that formal appropriability is often complemented with informal protections, existing studies have not extensively investigated how these different strategies are combined. Several studies have documented the importance of informal strategies such as lead time and rapid innovation (versioning), in allowing firms to appropriate value. To our knowledge, there are no extant studies that focus on the combination of different strategies in digital markets, and in particular how the use of these combinations varies across firms of different sizes.

2.2. The nature of digital goods and protection strategies

The discussion above outlines the broader literature within the settings where appropriability strategies have traditionally been studied, such as manufacturing. However, digitization and the emergence of digital platforms has shifted a considerable share of innovation to these settings. Given that formal IPR was not designed to protect digital technologies, which are easily copied, reproduced, and imitated (Shapiro and Varian, 1998; Greenstein et al., 2013; Goldfarb et al., 2015), we expect that appropriability strategies differ considerably in digital industries and on digital platforms.

The shift to digitalization is largely driven by increasingly low computing and development costs. For instance, small mobile devices, such as smartphones and other smart devices (i.e., wearable watches and smart thermostats), have computing power comparable to computers from just fifteen years ago. This growth in the availability of computing power, in a range of different settings, has enabled a greater scope for innovation than what has been previously possible. For instance, smartphones and smart thermostats are now capable of performing new and complex functions.

The scope for developing digital innovations has been accelerated by the emergence of digital platforms, such as the Apple App store and Android market, which provide an infrastructure for third-party developers to create innovations for these smart devices. These platforms provide access for third-party complementors to develop software apps, as well as supporting distribution, marketing and sales functionality.

An important feature of these platforms is that they greatly reduce the costs of developing digital innovations. This lowers the cost of creating a "minimum viable product"and, in turn increases the variety of different innovators that may want to enter onto the platform. Digital platforms allow developers to create and distribute products even if they are expecting to generate low, or even in extreme cases zero, direct monetary rewards. This can create a seemingly unending variety or long tail of products (Brynjolfsson et al., 2010, 2011). However, lowering the barrier to entry can greatly increase the pool of potential competitors and so create considerable scope for especially intensive competition, copying, and "business stealing" among digital innovators (Sundararajan, 2004; Tunca and Wu, 2013).

The low costs of innovating on digital platforms are further reduced by the knowledge, data, and content that is made readily available through digital technologies. For instance, through APIs individuals have access to a "firehose" of data that at low cost can be used to create complex and data-rich innovations. Readily available programing tools and libraries can be used to create complex technologies with relative ease. This creates scope for rapid innovation and experimentation. At the same time, the low costs of innovating on digital platforms imply lower replication costs, which allow competitors to imitate and replicate existing innovations (Shapiro and Varian, 1998). As a result, it becomes important to understand how developers can protect and appropriate value from digital innovations when these are so easily copied and replicated (Greenstein et al., 2013; Goldfarb et al., 2015).

2.3. Importance of IP for digital platforms

A defining characteristic of platforms and platform companies is that the value of the platform increases with the availability of complementary products (Rochet and Tirole, 2006; Parker and Alstyne, 2005). For instance, the value of social media sites grows with the number of users and the value of a smartphone operating system grows with the number of complementary apps. A central, but largely unexplored, element for a platform to attract such third parties to develop complementary products is for the platform to create conditions for complementors to be able to profit, or appropriate value, from their innovations, providing incentives to develop complementary products (Boudreau, 2012; Boudreau and Hagiu, 2008). In the broader economy, the ability for innovators to appropriate value is facilitated through property rights such as patents, copyrights, and trademarks. However, there may be informal strategies in use, as has been discussed. On digital platforms, the use of such property rights may be controlled and regulated, or at least shaped, by the platform owner (Parker and Alstyne, 2017). For instance, many platforms choose to define the legal rights that govern their marketplace (Boudreau and Hagiu, 2008). Similarly, platforms may choose to define the conditions in which a third party has exclusive rights to enter a marketplace.

Existing studies of appropriability on platforms have so far considered the competitive threats of the platform itself in appropriating the value from a third-party complementor (Gawer and Henderson, 2007; Huang et al., 2012; Parker and Alstyne, 2017) and how complementors may respond to such an action (Foerderer et al., 2018; Wen and Zhu, 2017). However, a perhaps greater concern facing complementers on a digital platform is copying or imitation of successful innovators that may occur as competitors enter the market. While developers on a digital platform may utilize the same types of appropriability strategies that are commonly used in other settings (Cohen et al., 2000), the degree to which different strategies are used may differ considerably, particularly because of the large number of small firms that are present in the digital platforms context.

2.4. Appropriability by small firms on digital platforms

The literature on appropriability has identified a menu of different appropriability strategies that are thought to be the primary means through which innovators may limit competition and appropriate value from their innovations. We focus on the strategies identified by earlier studies (Teece, 1986; Cohen et al., 2000; Levin et al., 1987), namely, formal protections, such as patents, registered copyright, and trademarks, and informal protections, such as rapid innovation and early-entry advantages. These strategies are often characterized as formal and informal; formal protections often rely on some form of legal intellectual property right, while informal protections are a form of strategic maneuvering relative to competitors (Teece, 1986).

An important determinant of which strategies are used is the relative cost of implementing these strategies. For instance, formal protection strategies, such as patents, registered copyrights, and trademarks, are costly to acquire and enforce. Alternatively, informal strategies, such as lead time and rapid innovation, are less costly to implement, particularly in a digital setting, where the costs of innovating are low. Therefore, we expect that on average, formal IPR, such as patents, copyrights, and trademarks might be observed to be less used than informal protections such as rapid innovation or early-entry advantages. We also expect that the use of formal and informal protections varies considerably across firms, in particular between firms that are large and have considerable resources to acquire and enforce IPR and smaller firms that have more limited means to acquire and enforce IP (Graham et al., 2009; Leiponen and Byma, 2009).

Here we ask how the use of different appropriability strategies may correlate with different firm characteristics, particularly firm size. Existing studies have found that firm size is an important determinant of how firms can protect their innovations (Leiponen and Byma, 2009; Graham et al., 2009), largely because firm size is indicative of firm assets. For instance, smaller firms have less access to financial, product development, and marketing assets. This may be particularly true for digital marketplaces, where competition is intense and expected returns from innovation are low. Weighed against the relatively high cost of acquiring and enforcing IPR, this suggests that patents, copyrights, and trademarks may not be a suitable means for these smaller developers to protect and appropriate value from their innovations. A plausible consequence would be that these smaller developers who are unlikely to protect their innovation through formal IP (patents, copyrights & trademarks), will choose to do so only through informal means –if any at all.

While we would expect that formal protections (or IPR) are more commonly used by larger companies, these companies may also make use of informal strategies. For instance, firms that pursue patents or copyrights may naturally also enjoy lead-time advantages resulting from early entry. As a result, appropriability strategies may be used in combination. On the basis of the above reasoning, we therefore broadly expect that small-scale developers will be less likely to rely on formal intellectual property rights than larger developers but that both may rely on informal appropriability strategies.

In terms of the overall use of different appropriability strategies at the level of the platform as a whole, where we expect that the overwhelming majority of developers are small firms (many even with only one or two employees), our earlier arguments would imply that the overall use of formal protection strategies may be considerably lower than what has been found in earlier studies (e.g., Cohen et al., 2000). Additionally, the predominant protection strategies in this context are likely to be informal. However, to what extent informal strategies are used and the extent to which different appropriability strategies are used in combination are empirical questions.

3. Empirical context

In the analysis that follows, we will use data on appropriability strategies from third-party developers creating apps for the Apple iOS platform. The Apple iOS platform is a software operating system that runs on Apple devices (iPhone, iPad, iPod). Apple only allows third-party software to be installed on these devices through its official storefront, the Apple App Store. Since the App Store was created in 2008, more than 2.4 million apps have launched on the storefront, and developers have generated more than US$130 Billion in revenue through either the sales of their apps or in-app purchases and subscription sales. In addition to the sheer volume of sales on the Apple App Store, this storefront includes apps by companies from a wide range of the broader economy. For instance, there are many companies that do not consider themselves to be software developers but rather social networks (Twitter, Instagram, etc.), which release their software on the Apple App Store and for whom the iOS platform is an important outlet for their products. There are of course many pure developers, which create only software apps such as games and productivity tools.

Several features make the Apple App Store an important context for studying the appropriability strategies of digital innovators. First, it hosts a wide range of different categories, from productivity to gaming and internet services. As a result, the Apple App Store is representative of digital innovators in the digital economy and an important context for studying digital innovation (Bresnahan et al., 2015; Yin et al., 2014). Second, this storefront allows developers to use US patent, copyright, and trademark rights to protect their innovations. Even in the case of international developers, the rules of the marketplace require that developers comply with US property right laws. Therefore, the App Store has relatively consistent legal conditions for all developers to acquire legal protection. Third, it is possible to observe the full population of developers and individual product titles for the entire app store. This makes it possible to account for biased sampling and ensure that the analysis is reflective of the overall sample.

3.1. Data collection

The challenge in studying appropriability strategies is that, with the exception of patents or trademarks, it is difficult to directly observe the appropriability strategies that are being used by firms in an industry. As a result, the primary approach for measuring the appropriability strategy of developers in marketplaces has been through surveys (Levin et al., 1987; Cohen et al., 2000; Graham et al., 2009). We first collected information about the entire population of developers and apps on the Apple App Store between 2009 and 2014. This allowed us to obtain information about more than 800,000 app developers (approximately 30,000 of which provided email contact information). This observational information not only provided contact information but also allowed us to account for population-level differences in the use of appropriability strategies (as described at the end of this section).

A typical limitation of surveys is partial, non-random sampling. A first, if imperfect, step we take toward reducing this problem is simply sampling as broadly as possible. We contacted roughly thirty thousand app developers via email. This subset was simply according to those app developers who listed an email address on the Apple App Store website.

Of these, we received completed surveys from 809 developer firms. The group represents 9,152 individual apps across 24 app categories. This is a relatively high number of respondents in comparison to many survey studies in management and social science and those studying appropriability strategies (Levin et al., 1987; Cohen et al., 2000; Graham et al., 2009). However, the arguably larger and more important point is that this sample size reflects only a small proportion (Approx. 3%) of those invited to participate and a even smaller proportion of the overall population of app developers (0.6%), similar to other survey-based research of appropriability strategies used across the economy or studies of online activity within a larger population. Therefore, our approach must recognize that there is abundant scope for nonrandom sampling in the initial harvesting of email addresses in relation to the population as well as in the choice to respond to the survey. In Section 4.1, we describe how we account for this bias in sampling.

3.2. Variable construction and definitions

We consider the appropriability strategies based on the mechanisms that were used in the highly influential papers (Cohen et al., 2000; Levin et al., 1987; Graham et al., 2009) that have established the literature on "how firms protect their intellectual assets." Doing so allows us to compare our results to those of earlier studies. From the survey responses, we observe whether a firm used patents, copyrights, trademarks, early entry, or versioning. Versioning is the process of revising and re-releasing software apps and can be thought of as the digital analog to rapid innovation. We use these terms interchangeably. [1]

We define the key covariates to be used in the analysis as follows. These are referred to as *BASIC CONTROLS* in later sections of the paper. We define *Market Tenure* as the number of months that a developer has been in the marketplace since its initial product launch. We define *Promotion Channel* as an indicator for whether a firm uses its app on the Apple App Store as a promotion channel for an alternative business, such as an airline app or mobile banking app. We define *US Based* as an indicator for whether the firm is based primarily in the United States. We define *Hobbyist Motivation* as an indicator for whether the developer reported that they develop software as a hobby rather than as their profession. This also serves as a proxy for whether a developer is looking to capture monetary profits. We define *BM: Licensing* and *BM: App Revenue* as indicators for whether a developer has reported that they generate revenue from licensing the technology in their app to others and an indicator for whether they attempt to generate revenue from selling or monetizing their application, respectively. These variables capture whether developers have an intention to profit from their innovations.

We also identify key controls using the Double LASSO procedure inspired by Belloni et al. (2013, 2014) as described in later sections. The key control variables as identified by that procedure are defined as follows. We define *Source of Innovation - Users* as an indicator for whether the developer reported using "users" as a source of inspiration for their innovative ideas. We define *Diff: Network Effects* and *Diff: Special Tech* as indicators for whether the developer reported "attempting to foster network effects" or "making use of special technologies" as strategies to differentiate their products from competitors, respectively.[2]

Descriptive statistics for these variables are shown in Table 1.

[1] The use of patents, copyrights and trademarks follows use in what was surveyed in earlier studies. Early entry were often referred to as lead-time advantages in the earlier surveys. Versioning is analogous to the "rapid" or "continuous" innovation constructs used in earlier surveys. We adapted this to be versioning because it is more indicative of the digital phenomenon that we are studying.

[2] The corresponding survey questions are responses to Question 12 from the survey instrument, shown in the Appendix C.

4. Empirical analysis and results

4.1. Estimating the overall use of appropriability strategies

A key contribution of earlier papers (Levin et al., 1987; Cohen et al., 2000; Graham et al., 2009; Hall and Sena, 2017) has been documenting the incidence at which different types of intellectual property rights are used. We begin by estimating the incidence of IPR strategies within the Apple App Store.

Correcting for Bias in Sampling and Sample Construction. We have information about the 1.2 million software titles available on the Apple App Store as of 2013 and information about appropriability strategies from those developers that responded to our survey. There is, of course, a concern that sample responses are nonrandom and not representative of the overall population. In many contexts where researchers cannot observe the entire population of potential firms, researchers ensure that their survey is randomly allocated to all firms and hope to receive a sufficiently large number of responses to be able to generalize their results. In settings such as this, where, by design, it is difficult to approach all respondents in such a way that they are likely to respond, but where there is data on the broader population (e.g., Manski and Lerman, 1977), it is possible to use sampling weights to correct for the fact that the sample may be nonrandom, therefore biasing our resulting analysis (Wooldridge, 2010). We use sampling weights calculated based on the category (genre), price of the apps, average rating of the products, number of products the developer has released, and the market tenure (the number of days since first release) of the developer. The distribution of each of these variables over the sample and population are shown in Fig. 1.

The key requirement for our reweighing strategy is that our sample covers the same types of firms as the population, even though there may be different densities.

The graphs in Fig. 1 demonstrate that that our samples exhibits coverage in terms of product and developer characteristics comparable to that of the overall population. For instance, in terms of average product rating, our sample covers product with ratings ranging from one to five. Nevertheless, it is clear that the distributions of the sample and population are not identical. For instance, the distribution of the *Number of Applications* suggests that we are over-sampling developers that release multiple titles and possibly larger companies. Similarly, our distribution for market tenure (*N Days in the Market*) has a higher share of younger firms than the overall population. However, because we have information about how our sample corresponds to the distribution of the overall population, we are able to weight our sampling (as described above) to correct for our nonrandom sample and to ensure that our analysis is generalizable to the broader population. Reweighing allows us to generate bias-corrected population-level estimates of the incidence of different appropriability mechanisms.

Overall Use of Appropriability Strategies. In Fig. 2, we present the raw results of our survey, alongside the reweighed population-level estimates. The sample proportions and population estimates are comparable, suggesting that sampling bias does not greatly affect our results. The population-level estimates in Fig. 2 show that patents and copyrights are used infrequently (13% and 23%, respectively) compared to other strategies, such as trademarks, versioning, and early-entry (28%, 43%, and 48%, respectively). The use of patents is considerably lower than the rates found by earlier studies on manufacturing settings (e.g., Cohen et al. 2000 find that 34.8% of firms use patents to protect their product innovations). Although, earlier studies have not reported the exact incidence of copyrights and trademarks, in earlier studies, the aggregate report for the use of other (non-patent) legal protections (20.7% in Cohen et al., 2000) is slightly lower but comparable to our findings in the digital platform context (31%). Perhaps most important is that most firms (67%) do not use legal protections for their innovations. Instead, firms appear to rely more heavily on informal protection mechanisms, such as early entry and rapid

Table 1
Descriptive statistics.

	Variables	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	*Patents*	0.11	0.31	1.00												
(2)	*Copyrights*	0.17	0.38	0.32	1.00											
(3)	*Trademarks*	0.26	0.44	0.36	0.47	1.00										
(4)	*Early Entry*	0.41	0.49	0.14	0.14	0.17	1.00									
(5)	*Versioning (Rapid Innovation)*	0.39	0.49	0.10	0.17	0.09	0.15	1.00								
(6)	*FORMAL*	0.34	0.47	0.49	0.63	0.84	0.19	0.12	1.00							
(7)	*INFORMAL*	0.61	0.49	0.08	0.13	0.14	0.67	0.65	0.15	1.00						
(8)	*Size: 1 Employee Firm*	0.23	0.42	−0.13	−0.13	−0.15	−0.09	0.01	−0.18	−0.03	1.00					
(9)	*Size: 2 Employee Firm*	0.13	0.34	−0.05	−0.07	−0.03	0.04	−0.01	−0.05	0.05	−0.21	1.00				
(10)	*Size: 3 − 10 Employee Firm*	0.30	0.46	0.10	0.08	0.11	0.07	0.04	0.16	0.07	−0.35	−0.25	1.00			
(11)	*Size: > 10 Employee Firm*	0.14	0.35	0.24	0.29	0.27	0.14	0.13	0.29	0.09	−0.22	−0.16	−0.26	1.00		
(12)	*Market Tenure (Months)*	32.38	13.66	−0.03	−0.09	−0.01	0.06	0.04	−0.03	0.09	0.12	0.01	−0.14	0.02	1.00	
(13)	*Promotion Channel*	0.11	0.31	0.06	0.08	0.09	0.02	−0.01	0.13	0.00	0.00	0.02	−0.02	0.04	−0.09	1.00
(14)	*US Based Company*	0.37	0.48	0.01	0.03	0.04	0.05	−0.03	0.01	−0.02	0.03	−0.01	−0.06	−0.06	0.14	−0.05
(15)	*Hobbyist Motivation*	0.11	0.31	−0.11	−0.12	−0.15	−0.08	−0.10	−0.18	−0.11	−0.19	−0.14	−0.23	−0.14	−0.01	−0.06
(16)	*BM: Licensing*	0.11	0.31	0.20	0.10	0.16	0.15	0.07	0.16	0.11	−0.10	−0.09	0.16	0.16	−0.12	0.13
(17)	*BM: App Revenue*	0.76	0.42	−0.15	−0.09	−0.09	−0.05	0.11	−0.09	0.04	0.15	0.05	0.00	−0.22	0.11	−0.11
(18)	*Source of Innovation - Users*	0.46	0.50	0.08	0.04	0.09	0.11	0.20	0.08	0.21	0.04	−0.02	−0.03	0.08	0.06	0.05
(19)	*Diff: Network Effects*	0.18	0.39	0.11	0.18	0.20	0.17	0.22	0.21	0.18	−0.08	−0.03	0.12	0.14	−0.03	0.12
(20)	*Diff: Special Tech*	0.15	0.36	0.09	0.10	0.09	0.27	0.05	0.09	0.16	0.01	0.00	0.03	0.15	0.02	0.06
				(14)	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**	**(23)**	**(24)**	**(25)**	
(14)	*USA based*			1.00												
(15)	*Hobbyist Motivation*			0.09	1.00											
(16)	*BM: Licensing*			−0.06	−0.10	1.00										
(17)	*BM: App Revenue*			−0.02	0.00	−0.11	1.00									
(18)	*Source of Innovation - Users*			0.07	−0.01	0.10	0.06	1.00								
(19)	*Diff: Network Effects*			0.00	−0.12	0.13	0.01	0.11	1.00							
(20)	*Diff: Special Tech*			0.06	−0.11	0.13	−0.04	0.13	0.14	1.00						

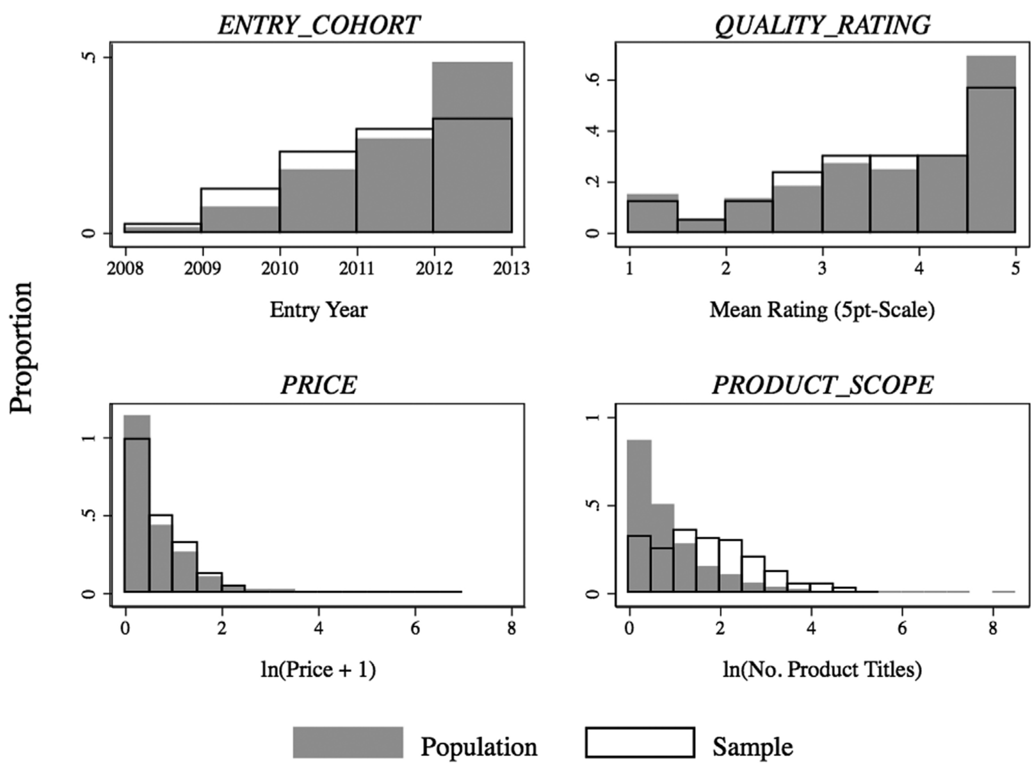

Fig. 1. Comparison of Sample and Population across observed variables.

innovation. It is important to highlight that the numbers that we observe here for the use of informal strategies are comparable to the numbers found in earlier studies (52.8% in Cohen et al. 2000). This suggests that informal strategies may be as important for small firms, in a setting such as the Apple App Store, as they are for large manufacturing firms.

4.2. Clustering of formal and informal strategies

While these strategies may be important individually, we expect that developers use multiple appropriability strategies in concert to protect their innovations. To explore this, we analyzed how the strategies that we study (patents, copyrights, trademarks, early-entry, and versioning) cluster in the data.

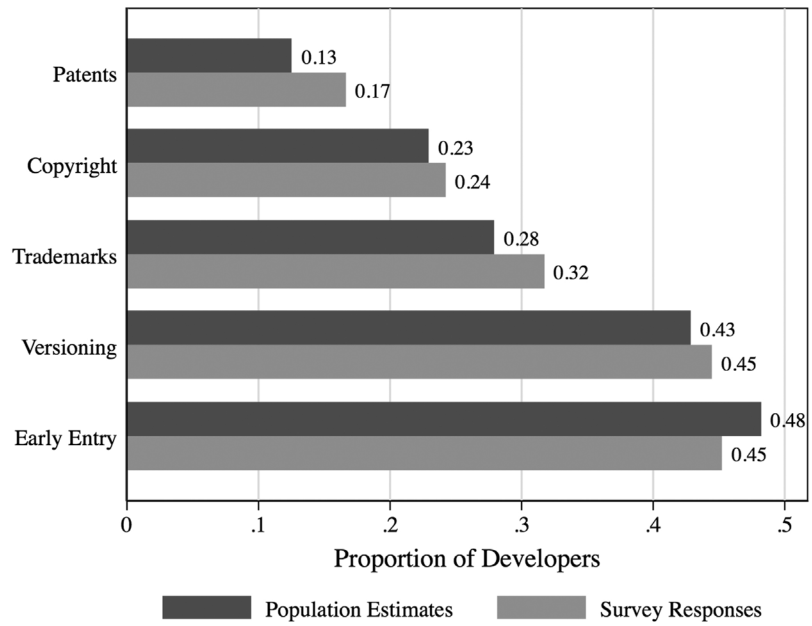

Fig. 2. Reported use of different appropriability strategies (sample & population estimate).

Using principal component analysis, we find that there are two overall clusters of appropriability strategies: firms that use only informal (lead time and versioning) strategies and firms that use a combination of formal (patents, copyrights, and trademarks) and informal strategies. (Screen plot and cluster weights are shown in Appendix B.) Given this clustering of formal and informal strategies, we create two outcome variables to use in our analysis. *FORMAL* is a dummy variable that indicates whether a firm uses patents, copyrights, or trademarks. *INFORMAL* is a dummy variable that indicates whether a firm uses lead time or secrecy. Approximately 36% of developer firms use only *INFORMAL* strategies, while only 9% use only *FORMAL* strategies; 24% of firms use a combination of both strategies.

4.3. Appropriability strategies by firm size

We model the choice of using a protection mode as a function of the size of the firm. The basic model guiding our empirical analysis is as follows.

$$\Pr(\text{PROTECTION}) = \alpha + \text{SIZE}\beta + \text{CONTROLS}\gamma + \text{CATEGORIES}\delta + \epsilon \tag{1}$$

The outcome variable is an indicator for *FORMAL* or *INFORMAL* strategies or both. *SIZE* is a vector of dummy variables that indicate the size of the firm from the set of potential categories (i.e., < 1 full-time employee, 1 full-time employee, 2 full-time employees, 3–10 full-time employees, and > 10 full-time employees). Our survey also captures whether firms have more than fifty employees. However, since there are no firms of that size that use only informal strategies, we could be concerned that this lack of variation would bias our results. As a result, we construct our size variable to indicate whether firms have ten employees or more.

In our model, we control for unobserved differences across different types of apps by including a vector of dummies for each category where a developer is present, indicated by *CATEGORIES*. In addition, we introduce several controls (referred to as *BASIC CONTROLS* in the results tables) to account for additional factors that may confound our analysis (as described in Section 4.1). We control for the fact that a developer may be a hobbyist and may not be attempting to protect his or her innovation by controlling for whether a developer reported that “developing software as a hobby” was an important motivation. We control for the fact that a firm may not be purely a software developer and may instead use the app as a promotion channel for an offline business. We control for the market tenure of firms by controlling for the number of days since the firm first entered the marketplace. We also control for whether a firm is attempting to generate revenue by licensing their technology or whether a developer wants to generate revenue at all, as these may determine whether a developer has any desire to protect its innovation.

An important factor to consider is that there are likely to be several additional controls that may influence appropriability strategy choices. For example, motivation to profit may influence the choice of how firms protect (Lakhani and Wolf, 2005; Harhoff et al., 2003) or the source of innovation may correlate with the need to protect (Laursen and Salter, 2014). While these factors are not the direct focus of our study, it may be important to control for them, and the survey data allows us to capture much of this information. However, simply introducing a full battery of potential covariates may greatly reduce the accuracy of our estimates while not adequately accounting for potential biases.

To select an appropriate subset of control variables, we implement the Double LASSO algorithm developed by Belloni et al. (2014). The LASSO algorithm is a variation of the least squares regression approach that performs shrinkage (reduction of coefficient size) and selection (removal of variables with low statistical power). The conventional LASSO approach (Tibshriani, 1996) results in a linear regression with a subset of the most statistically important variables; however, this also affects the magnitude of the coefficients and we would not be able to directly interpret the coefficients or standard errors of such a model. The Double LASSO is a two-stage regression approach that uses the LASSO regression to regress the outcome variable and main variable(s) of interest against the set of potential control variables. The selected coefficients are then included in a second stage (regular OLS or Probit) regression.[3] This approach provides the benefit of variable selection

[3] The LASSO regression is a variant of the OLS regression that deliberately reduces the coefficients (often referred to as a shrinkage estimator) based on a pre-specified shrinkage factor (often denoted λ). In our case we allow the λ is determined by the DOUBLE LASSO algorithm (Belloni et al., 2013, 2014). Unlike OLS regression where the objective function of the estimator is to minimize the residual sum of squares (RSS), the LASSO estimator includes an additional term in the objective function ($\text{OBJECTIVE} = \text{RSS} + \lambda \sum_{i=0}^{M} |w|$), where w is the coefficient for each of M variables included in the model. As a result, the objective function includes a penalty for the size and number of

Table 2
Comparison of Sample and Population Means

Variable	Sample	Population	t-Stat.	(p - value)
Average Product Rating	3.48	3.55	3.83	(0.00)
Number of Product Ratings	569.20	432.78	−1.03	(0.15)
Days in Top 10 Ranking	1.55	2.71	1.36	(0.08)
Number of Apps Launched (by Developer)	12.04	4.61	−9.18	(0.00)
Price	2.59	1.80	−6.90	(0.00)
Days Since Initial Entry to Market	1020.68	1171.21	32.00	(0.00)

The above table compares all variables that are available for both the sample and population. t statistics are reported along with respective significance level. In instances where the t-statistic is positive, the significance level indicates the probability that sample mean is higher than the population mean. Alternatively, where the t-statistic is negative the significance level indicates the probability that the population mean is higher than the sample mean.

generated by the LASSO, but it does not affect the parameters of the standard errors and coefficients (via shrinkage). This approach is proposed as a way of controlling for potentially important covariates without running the risk of data mining or selectively introducing covariates.

Tables 2 and 3

In our LASSO regression, we include the full set of potential controls from our survey and observational data, including the number of apps the developer has released, as well as variables that indicate the source of the developers' ideas, their product differentiation strategy, their revenue model, their "openness" in terms of selectively revealing code or releasing their code as open source, and their personal motivation. This leads us to a set of forty-two potential control variables that we may want to include in the model in addition to our basic controls. We define these variables that are selected by the LASSO model as *ADDITIONAL CONTROLS.*

Multivariate probit regression results

Here we separately consider the use of formal and informal protection strategies. Since these two groups are not mutually exclusive, we use a multivariate probit regression to account for the potential correlation between these two outcome variables.

The results are reported in Table 4. We present the results for formal strategies in columns 1–4 and informal strategies in columns 5–8. In the first column for each outcome, we include only the firm size variables and category dummies. In the second column, we introduce the *BASIC CONTROL* variables. For those variables that are significant, we also report the point estimates and standard errors to show which variables are correlated with the use of different strategies. In the third column, we include the *ADDITIONAL CONTROLS* that were selected using the double LASSO method mentioned above. In the fourth column, we present the results reweighed by our sampling weights to ensure that our regression results are not drastically influenced by our sampling procedure.

Across columns 1 through 4, the results show that dummies larger firms (with 3–10 and more than 10 employees) are significant and positive relative to the baseline (firms with less than one full-time employee) for formal protection. However, for informal protections, the indicator variables for larger firms are not significant, and the coefficients are smaller in comparison. To interpret the magnitude of these effects, we present marginal effects of these models (columns 3 and 7) in Fig. 3. The use of informal strategies does not increase significantly with firm size. Approximately 53% of firms with less than one full-time employee use informal strategies, while 65% of firms with more than ten employees use informal strategies. However, for formal strategies, this increase is considerable. Approximately 22% of firms with less than one full-time employee use informal strategies, while 62% of firms with more than ten employees use informal strategies. This corresponds to an increase of 2.8 times the likelihood of using formal protection.

What is perhaps most important is that informal strategies are an important protection strategy for both small and large firms. Moreover, for larger firms, informal protection strategies appear to be used just as frequently as formal protection strategies. This further reinforces the notion that there exists a cluster of firms that use only informal strategies (seemingly smaller firms) and a cluster of firms that use a combination of formal and informal strategies (larger firms).

Multinomial Logit Regression Results

To specifically address the use of a combination of different strategies, we repeat the analysis by looking at mutually exclusive groups of protection strategies, namely, FORMAL only, INFORMAL only, both FORMAL and INFORMAL, and firms which do not use any protection. As the earlier cluster analysis suggests, firms that choose to protect their assets generally do so through only informal means or a combination of formal and informal means.

We re-estimate the model in expression (1) using a multinomial logit regression using a categorical variable to indicate whether a firm uses formal or informal protections only or a combination of the two. The results are shown in Table 4. As in the earlier models, the results are split into three groups for each of the outcome variables. The baseline outcome for these regressions is that the firm does not use any protection strategy at all.. Similar to the earlier results, the first column for each outcome introduces only the firm size variable. The second column introduces the basic control variables, the third column introduces the control variables selected by the double LASSO algorithm, and the fourth column presents the regression results, weighted using sampling weights. Because of the large number of controls that are included in these models, we do not report all the control variables in the main tables. Instead, we report only the control variables that are significant, in order to document which variables are correlated with our outcomes of interest.

The coefficients for dummy variables for larger firms (firms with 3 and 3–10 employees) are positive and significant (95% level) for both firms that use only formal protections and those that use a combination of formal and informal protections. The coefficient is positive but not significant for firms that use only informal protections. Regarding the control variables, firms that develop apps as a promotion channel for their non-app business (Defined *Promotion Channel* in Table 4) are more likely to use only formal protection. Firms that differentiate themselves based on special technology according to their survey responses (Defined *Diff Strategy: Special Tech* in Table 5) are more likely to use informal protections or a combination of formal and informal protections than to not use protecting strategies at all. Finally, those developers that generate ideas for new products from their users appear to rely more on informal strategies, while developers that attempt to build network effects around their products are more likely to use a combination of formal and informal strategies.

To interpret the magnitude of these effects, we examine the marginal effects for these models in Fig. 4. From the marginal effects, it is clear that the use of formal strategies increases with firm size, both alone and together with informal strategies. Smaller firms are more likely to use only informal strategies. However, with larger firms, only a small proportion choose to use formal strategies. Moreover, smaller firms are likely not to protect at all, while there is only a small share of

(*footnote continued*)
coefficients. Therefore, the estimator reduces the size of the coefficients but also sets the coefficients to zero if they fall below a threshold (this is specific to LASSO instead of other shrinkage estimators). The set of variables that are included in the LASSO are therefore the variables that are most predictive of the outcome variable. Because the lasso deliberately alters the magnitude of the coefficients, the results of the LASSO regression are not directly interpretable. However, the DOUBLE LASSO indicates which variables are suitable controls to be included in a regular regression model. The coefficients from that model can then be interpreted directly.

Table 3
Results of Multivariate Probit Regressions for Use of Formal & Informal Strategies

DV: *Indicator for FORMAL (Patents, Copyrights &Trademarks) and INFORMAL (Early Entry &Versioning).*

	(1) **DV: Formal Protection**	(2)	(3)	(4)	(5) **DV: Informal Protection**	(6)	(7)	(8)
Size: 1 Employee Firm	0.17	−0.02	−0.12	0.03	0.46*	0.49*	0.10	0.29
(0.22)	(0.26)	(0.25)	(0.27)	(0.19)	(0.25)	(0.22)	(0.25)	
Size: 2 Employee Firm	0.50*	0.33	0.15	0.34	0.50*	0.56*	0.35	0.24
(0.25)	(0.28)	(0.26)	(0.30)	(0.23)	(0.28)	(0.24)	(0.28)	
Size: 3 - 10 Employee Firm	1.13***	1.03***	0.63**	0.92***	0.64***	0.67**	0.29	0.36
(0.20)	(0.24)	(0.23)	(0.26)	(0.19)	(0.24)	(0.21)	(0.24)	
Size: 10+ Employee Firm	1.67***	1.51***	1.11***	1.19***	0.73**	0.81**	0.38	0.30
(0.24)	(0.28)	(0.28)	(0.31)	(0.23)	(0.28)	(0.27)	(0.30)	
Selected Control Variables								
App is Promotion Channel		0.73***	0.57**	0.68**		−0.08	−0.09	−0.16
	(0.21)	(0.19)	(0.22)			(0.21)	(0.19)	(0.23)
Diff. Strategy - Network Effects			0.41*	0.60**			0.31	0.42
			(0.17)	(0.19)			(0.18)	(0.22)
Source of Innovation - Users			0.10	0.12			0.24*	0.30*
			(0.13)	(0.15)			(0.12)	(0.14)
Diff. Strategy - Special Tech.			−0.02	0.01			0.53**	0.49*
			(0.17)	(0.18)			(0.18)	(0.21)
Controls Variables								
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic Controls		Yes	Yes	Yes		Yes	Yes	Yes
Additional (LASSO Selected) Controls			Yes	Yes			Yes	Yes
Constant	−1.08***	−1.25***	−1.11***	−1.14***	−0.27	−0.52	−1.19***	−0.79*
	(0.16)	(0.30)	(0.29)	(0.33)	(0.15)	(0.29)	(0.28)	(0.32)
χ^2	191.99	217.97	242.89	277.45	191.99	217.97	242.89	277.45
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
log likelihood	−559.50	−545.88	−652.64	−505.73	−559.50	−545.88	−652.64	−505.73

* Standard errors in parentheses. $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$). $N = 626$.

Table 4
Results of Multinomial Logit Regression for Probability of Using IPR

DV: *Indicator for use of Formal, Informal or Both.* **Baseline:** *Do Not Protect*

	(1) **Formal Protection**	(2)	(3)	(4)	(5) **Informal Protection**	(6)	(7)	(8)	(9) **Formal &Informal Protection**	(10)	(11)	(12)
Size: 1 Employee Firm	0.35	−0.37	−0.32	0.07	0.48	0.48	0.10	0.54	0.80	0.59	0.33	0.64
	(0.53)	(0.59)	(0.63)	(0.67)	(0.28)	(0.37)	(0.40)	(0.48)	(0.48)	(0.63)	(0.66)	(0.68)
Size: 2 Employee Firm	0.49	−0.27	−0.39	−0.24	0.75*	0.79	0.28	0.12	1.70***	1.61*	1.20	1.11
	(0.63)	(0.69)	(0.73)	(0.80)	(0.35)	(0.42)	(0.46)	(0.54)	(0.51)	(0.65)	(0.68)	(0.72)
Size: 3 - 10 Employee Firm	1.44**	0.98	0.78	1.29*	0.67*	0.77*	0.23	0.42	2.41***	2.38***	1.81**	2.24***
	(0.46)	(0.54)	(0.57)	(0.63)	(0.29)	(0.38)	(0.42)	(0.48)	(0.43)	(0.60)	(0.63)	(0.61)
Size: 10+ Employee Firm	2.55***	2.09**	1.33	1.68*	0.90	1.09*	0.12	0.23	3.62***	3.71***	2.60***	2.48**
	(0.59)	(0.66)	(0.74)	(0.82)	(0.48)	(0.54)	(0.61)	(0.70)	(0.54)	(0.69)	(0.75)	(0.77)
Controls Variables												
App is Promotion Channel	1.43**	1.17*	1.42*		0.12	−0.10	−0.27		1.04*	0.77	0.89	
	(0.48)	(0.52)	(0.57)		(0.40)	(0.45)	(0.54)		(0.41)	(0.47)	(0.56)	
Diff. Strategy - Network Effects			0.43	0.91			0.41	0.63			1.14**	1.65**
			(0.54)	(0.65)			(0.40)	(0.53)			(0.43)	(0.54)
Source of Innovation - Users			0.64	0.85			0.58*	0.81**			0.47	0.70
			(0.38)	(0.48)			(0.25)	(0.29)			(0.30)	(0.38)
Diff. Strategy - Special Tech.			0.63	0.97			1.39***	1.52**			1.11*	1.15*
			(0.58)	(0.69)			(0.41)	(0.51)			(0.46)	(0.56)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BASIC CONTROLS		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
ADDITIONAL (LASSO) CONTROLS		Yes	Yes			Yes	Yes			Yes	Yes	
Constant	−1.72***	−1.84**	−1.73*	−1.95*	−0.41*	−1.13*	−1.83***	−1.34*	−2.11***	−3.30***	−3.83***	−3.13***
	(0.39)	(0.67)	(0.73)	(0.87)	(0.21)	(0.46)	(0.55)	(0.64)	(0.38)	(0.70)	(0.77)	(0.80)
χ^2	210.01	250.02	358.87	2276.34	210.01	250.02	358.87	2276.34	210.01	250.02	358.87	2276.34
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
log likelihood	−708.17	−688.16	−633.74	−486.98	−708.17	−688.16	−633.74	−486.98	−708.17	−688.16	−633.74	−486.98

* Standard errors in parentheses. $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$. $N = 626$.

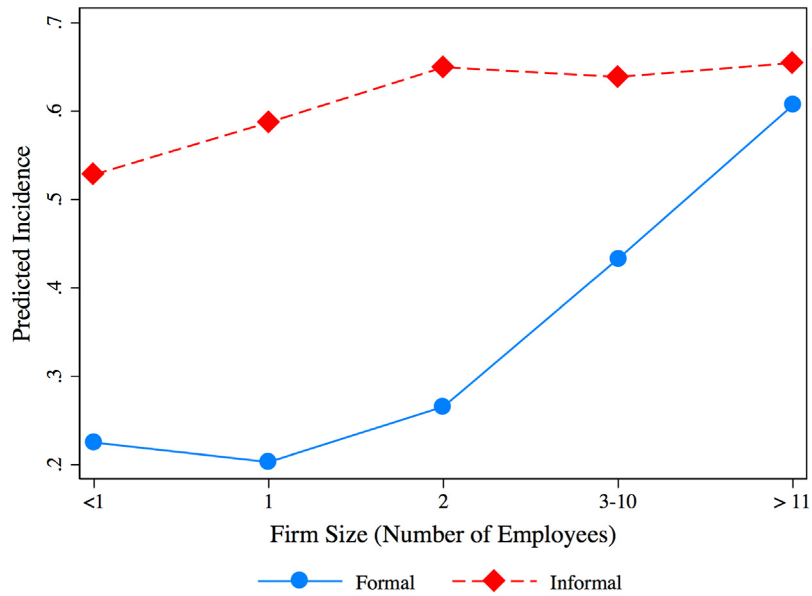

Fig. 3. Marginal effects for incidence of formal and informal strategies.

larger firms that do not protect their innovations.

The control variables also suggest that protection strategies are correlated with several firm characteristics. For instance, firms that attempt to differentiate themselves through network effects are more likely to use a combination of formal and informal strategies. Similarly, firms that differentiate themselves through "special technology", as is described in the survey, tend to protect their innovation through informal strategies or a combination of formal and informal strategies, rather than simply using formal protections. Alternatively, firms that source ideas for their innovations from users are likely to use only informal strategies to protect their innovations, while there is no significant effect for formal protections.

Multivariate Probit Results for Individual Appropriability Strategies

We disaggregate our earlier measures of formal and informal strategies into individual appropriability strategies (patents, copyrights, trademarks, lead time and versioning (i.e., Rapid Innovation)). Since these strategies are not mutually exclusive, we again use a multivariate regression to estimate their incidence with varying levels of firm size. In Fig. 5, we present the marginal effects with respect to firm size. The individual regression results are given in Appendix B.

The results for informal strategies (lead time and versioning) is overall consistent with the clustered results. These strategies are used slightly more frequently by larger firms. However, even the smallest firms use them relatively infrequently. Alternatively, for formal strategies (patents, copyrights, and trademarks), there is an increase in the use of these strategies with firm size. Smaller firms are far less likely to utilize these strategies than are larger firms.

Additional specifications and robustness

We performed several additional tests to demonstrate the robustness of the regression results, including using sampling weights for the regression to correct for biased sampling, for the full sample of 809 firms for which we are able to observe both *IPR* and *BASIC CONTROLS* and the smaller subset of 626 firms for which we observe the full set of

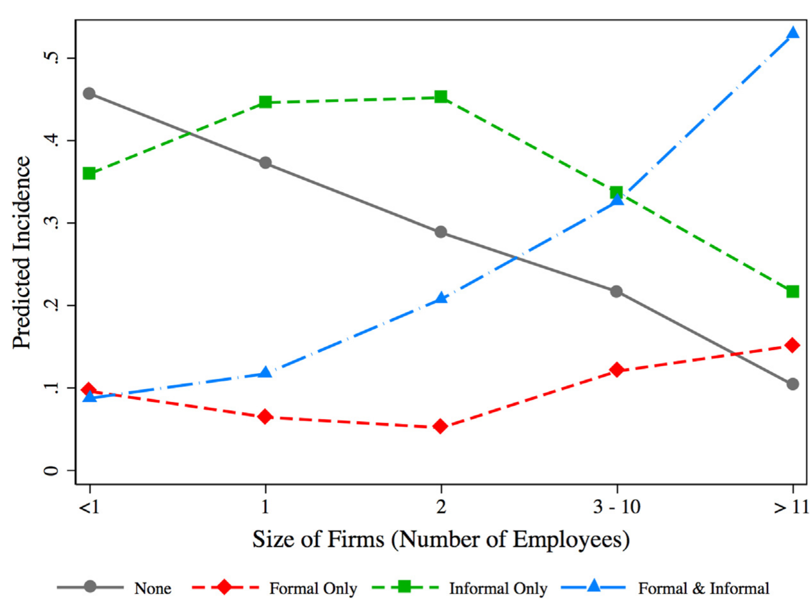

Fig. 4. Marginal effects for multinomial logit regressions.

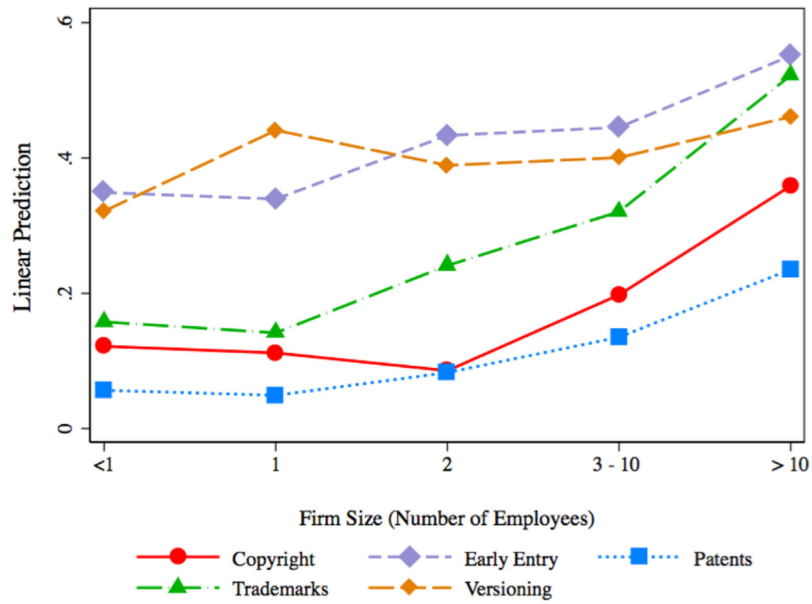

Fig. 5. Marginal effects for multivariate probit regressions (individual protection strategies).

ADDITIONAL CONTROLS (all 18 variables). Similarly, the overall results of our clustering strategy are robust to alternative clustering methods (K means, K medians, LDA, etc.). In each case, the clusters conform to groups of formal and informal clusters, and in some cases, the intersection of these two sets.

The introduction of the LASSO-selected control variables did not greatly impact the results of the analysis, as the variable selected were those that most highly correlated with either the outcome or explanatory variables. For instance, the *App is Promotion Channel* variable was correlated with the use of formal protections and only accounts for 11% of apps. These are companies that are not predominantly app developers but are using the app as a promotion channel for their main business.[4] Similarly, the *Source of Innovation – Users* variables, which indicates whether the ideas for their innovations come from "user innovators," indicates that 46% of innovators are gaining ideas from their users. This suggests that innovation in this setting is highly dependent on interaction between innovators and end users. Approximately 42% of respondents in our survey report being end-users, although this does not correlate sufficiently with appropriability strategies to be included by the LASSO algorithm.[5]

5. Discussion and conclusion

There has been a long-standing general interest in research on appropriability (Teece, 1986; Laursen and Salter, 2014; Cohen et al., 2000) running parallel to, but separate from, a rapid expansion of research on digitization of the economy and digital platforms, more specifically. The broader literature on digitization (Greenstein et al., 2013; Yoo et al., 2010; Nambisan et al., 2017) has explored how the growing shift toward digital innovation is affected by existing institutions, such as IPR. The present paper builds on this stream of work by empirically examining how innovators on a digital platform appropriate value from their innovations. The ability of innovators to appropriate value from their innovation is particularly important in the context of platforms, because it directly relates to their incentives to join the platform in the first place. Therefore, the question of appropriability is at the heart of the issue of platform strategy (Gawer and Henderson, 2007; Huang et al., 2012; Parker and Alstyne, 2017). However, the innovators on these digital platforms are often far smaller firms than typically found in other settings. For example, more than 43% of the developers in our sample had one or fewer full-time employee.[6] While earlier studies have looked at appropriability by smaller firms (Leiponen and Byma, 2009; Graham et al., 2009), they have not explored the protection strategies used by the smallest of firms, such as those that can be found on digital platforms.

While these smallest firms are often given less attention in the research, the results of the present study suggest that they represent a sizable share of the overall apps marketplace. When we consider that these developers contribute to the "long tail" of complementary products accounting for almost US$130 Billion in revenue, we can expect that these small developers constitute an economically important share of this marketplace. Additionally, the ability of these small firms to limit competition and profit from their innovation so that they may grow into larger firms relates to a broader set of questions about the entrepreneurial strategies of firms in these platform markets. While the present paper does not explore all possible strategies, our inquiry offers insights into those strategies that are commonly used and that have been most commonly studied.

Our study documents the use of appropriability strategies by developers on a digital platform and how the use of these strategies differs for smaller firms, compared to the larger firms that have been typically studied. We provide evidence that appropriability strategies used by developers on the Apple App Store cluster into formal and informal protections. A large majority of firms (more than 70%) take measures to protect their innovations in some way, with many using only informal strategies (36.76%) and a smaller subset using a combination of formal and informal strategies (24.12%). We found that merely a fraction of all firms (9.71%) employ only formal protections. Looking into specific protection strategies, we find that patents are seldom used (approximately 13% of firms), while versioning (or rapid innovation) and early entry are used by more than 40% of firms. This suggests that patents are not the most important appropriability lever for firms in this setting but that there is a non-negligible amount of patenting being done. In

[4] Examples of this include airlines that use apps for check-in, or restaurants that allow customers to order through their apps.

[5] This is not shown in the tables but is based on the fact that 42% of developers reported that "use need" was an important motivation for them to develop innovations.

[6] As reported in the descriptive statistics, 20% of developers have less than one full time employee and 23% have only one full time employee.

comparison, Graham et al. (2009) found that 24% of software firms that do not acquire venture capital funding are likely to patent.[7]

In line with our arguments, we find that firm size is an important factor in determining the choice of protection strategies. We find that informal strategies (early entry and rapid innovation/versioning) are used extensively by both large and small firms, while we found that formal IPR protections (patents, copyrights, and trademarks) are used mainly by larger firms. These results hold for both the use of formal and informal protections, and for individual protection strategies. Our results show that informal IPR protections are used by very small firms and part-time developers, while for larger firms, informal protections are important when combined with formal protections.

Theoretical Implications. The results of this paper make several theoretical contributions. First, the literature on technology platforms has demonstrated that a vital determinant of the success of technology platforms is creating conditions for outside innovators to both create and capture value by joining the platform (Parker and Alstyne, 2005; Gawer and Cusumano, 2014; Gawer, 2014; Boudreau, 2010). However, there has been far less inquiry into how these innovators on these platforms may protect themselves from competitive pressures and appropriate value. The results of this paper help to deepen our understanding of how platforms may shape the population of third-party developers that they attract (Cennamo and Santalo, 2013; Boudreau and Hagiu, 2008; Corts and Lederman, 2009; Zhu and Iansiti, 2012), based on the types of appropriability strategies that are available. This study directly relates to the question of how innovators "stimulate externally developed innovation that complements the platform" (Gawer and Cusumano, 2014).

Second, this paper contributes to the literature on appropriability by considering the use of appropriability by small companies on digital platforms.. The literature on appropriability has examined how companies protect their innovations in a variety of settings. Most notably, this includes the highly influential studies by Cohen et al. (2000), Levin et al. (1987), Graham et al. (2009). These studies have exclusively considered either very large companies, predominantly in manufacturing and brick-and-mortar settings, or packaged software. We explore how innovators, predominantly very small firms, on a digital platform appropriate value from their innovations. As a growing share of economic and innovative activity shifts to platforms, this study helps to extend our understanding of how innovators in such a setting appropriate value and how this differs from what is known about manufacturing and more conventional settings.

Managerial and Policy Implications. Existing research has established that allowing innovators to protect their innovation and appropriate profits is an important factor in fostering innovation (Moser, 2005, 2013; Arrow, 1962); it is thus a vital concern for policy makers. Within a platform setting, this takes on its own set of conditions. Given that the success of platforms is so heavily predicated on the availability of complementary innovations (Parker and Alstyne, 2005; Rochet and Tirole, 2006), a critical concern for the platform is creating conditions so that third-party developers have the incentive to innovate on their particular platform. The famous case of Atari, where low barriers to entry led to intense competition and eventually diminished innovation, resulting in a collapse of the market, further reinforces this point (Boudreau and Hagiu, 2008). As a result, it is critical for such platforms to understand how innovators on their platform are able to appropriate value, so that platforms may design and enforce appropriate property rights.

From this perspective, understanding the relative importance and role of formal and informal property rights in allowing third-party developers to appropriate value may shape the policies that the platform chooses to enact. From the perspective of a platform regulator (Gawer and Cusumano, 2014; Parker and Alstyne, 2005; Cennamo et al., 2018; Ozalp et al., 2018), the objective is to grow the multiple sides of the platform. Knowing that formal property rights are used primarily by larger companies can allow the platform to determine the rules governing IPR such that they create conditions favorable to larger companies. An example of this may be ensuring that property rights such as patents, copyrights, and trademarks are strictly enforced.[8] Similarly, knowing that informal rights are used by both large and small developers suggests that creating the ability for developers to enter the platform easily and without frictions or to quickly innovate may be important for the incentives of both large and small developers to appropriate value on the platform. However, by creating conditions where informal strategies, such as early entry or versioning, may be easily implemented, the platform owner may be able to foster innovation by smaller developers. Such conditions might include easing the costs of innovating on the platform, or getting new products approved. Relatedly, if the platform owner wants to focus exclusively on having a long tail of very small scale developers, the present results suggest that formal property rights may not be critical to allowing such innovators to appropriate value.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.respol.2019.01.012.

References

Arora, A., Ceccagnoli, M., Cohen, W.M., 2008. R&D and the patent premium. Int. J. Ind. Organ. 26 (5), 1153–1179.

Arrow, K.J., 1962. Economic Welfare and the Allocation of Resources for Invention. In: In The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton University Press, New Jersey, NY. pp. 609–626.

Arundel, A., 2001. The relative effectiveness of patents and secrecy for appropriation. Res. Policy 30 (4), 611–624.

Belloni, A., Chernozhukov, V., Hansen, C., 2013. Inference on treatment effects after selection among high-dimensional controls. Rev. Econ. Stud. 81 (2), 608–650.

Belloni, A., Chernozhukov, V., Hansen, C., 2014. High-dimensional methods and inference on structural and treatment effects. J. Econ. Perspect. 28 (2), 29–50.

Bessen, J., Hunt, R.M., 2007. An empirical Look at Software Patents. J. Econ. Manag. Strategy 16 (1), 157–189.

Boudreau, K.J., 2010. Open Platform Strategies and Innovation: Granting Access vs. Devolving Control. Manag. Sci. 56 (10), 1849–1872.

Boudreau, K.J., 2012. Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation. Organ. Sci. 23 (5), 1409–1427.

Boudreau, K.J., Hagiu, A., 2008. Platform Rules: Multi-Sided Platforms as Regulators.

Bresnahan, T.F., Davis, J.P., Yin, P.-L., 2015. Economic Value Creation in Mobile Applications Chapter. In: Jaffe, A.B., Jones, B.F. (Eds.), The Changing Frontier: Rethinking Science and Innovation Policy. University of Chicago Press, pp. 233–286.

Brynjolfsson, E., Hu, Y.J., Simester, D., 2011. Goodbye pareto principle, hello long tail: the effect of search costs on the concentration of product sales. Manag. Sci. 57 (8), 1373–1386.

Brynjolfsson, E., Hu, Y.J., Smith, M.D., 2010. Long Tails Versus Superstars: The Effect of IT on Product Variety and Sales Concentration. Inform. Syst. Res. 21 (4), 1–20.

Cennamo, C., Ozalp, H., Kretschmer, T., 2018. Platform Architecture, Multihoming and Complement Quality: Evidence from the U. S. Video Game Industry. Information Systems Research.

Cennamo, C., Santalo, J., 2013. Platform Competition: Strategic Trade-offs in Platform Markets. Strategic Manag. J. 34, 1331–1350.

Cockburn, I. M. and Griliches, Z. (1987). Industry Effects and Appropriability Measures In the Stock Market's Valuation of R&D and Patents. NBER Working Paper Series.

Cockburn, I.M., MacGarvie, M.J., 2011. Entry and patenting in the software industry. Manag. Sci. 57 (5), 915–933.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not).

Corts, K.S., Lederman, M., 2009. Software exclusivity and the scope of indirect network effects in the U.S. home video game market. Int. J. Ind. Organ. 27 (2), 121–136.

Foerderer, J., Kude, T., Mithas, S., Heinzl, A., 2018. Does platform owner's entry crowd out innovation? Evidence from google photos. Inform. Syst. Res. 29 (2), 444–480.

Gans, J., Stern, S., 2017. Endogenous Appropriability. American Economic Review: Papers & Proceedings 107(5) 317–321.

[7] Software firms that do not acquire venture funding are an appropriate comparison group since firms in these app markets are unlikely to acquire VC funding (Hallen et al., 2017).

[8] Apple and Google have different policies about IP enforcement that directly shape the types of products released on their platforms.

Gawer, A., 2014. Bridging differing perspectives on technological platforms: Toward an integrative framework. Res. Policy 43 (7), 1239–1249.
Gawer, A., Cusumano, M.A., 2002. Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation. Harvard Business School Press.
Gawer, A., Cusumano, M.A., 2014. Industry platforms and ecosystem innovation. J. Product Innov. Manag. 31 (3), 417–433.
Gawer, A., Henderson, R., 2007. Platform owner entry and innovation in complementary markets: evidence from intel. J. Econ. Manag. Strategy 16 (1), 1–34.
Goldfarb, A., Greenstein, S.M., Tucker, C.E., 2015. Introduction. In Economic Analysis of the Digital Economy. University of Chicago Press, Chicago, pp. 1–35.
Graham, S.J.H., Merges, R.P., Samuelson, P., Sichelman, T., 2009. High Technology Entrepreneurs and the Patent System: Results of the 2008 Berkeley Patent Survey. Berkeley Technol. Law J. 24 (4), 1255–1327.
Greenstein, S., Lerner, J., Stern, S., 2013. Digitization, innovation, and copyright: What is the agenda? Strategic Organ. 11 (1), 110–121.
Hall, B.H., Sena, V., 2017. Appropriability mechanisms, innovation, and productivity: evidence from the UK. Econ. Innov. New Technol. 26 (1-2), 42–62.
Hall, B.H., Ziedonis, R.H., 2001. The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. RAND J. Econ. 32 (1), 101.
Hallen, B.L., Davis, J.P., Yin, P.-L., 2017. Entrepreneurial Bootstrapping and the Social Disconnection of New Organizations In the Mobile App Ecosystem.
Harhoff, D., Henkel, J., Von Hippel, E., 2003. Profiting from voluntary information spillovers: How users benefit by freely revealing their innovations. Res. Policy 32 (10), 1753–1769.
Huang, P., Ceccagnoli, M., Forman, C., Wu, D., 2012. Appropriability mechanisms and the platform partnership decision: evidence from enterprise software. Manag. Sci. 59 (September 2014), 102–121.
James, S.D., Leiblein, M.J., Lu, S., 2013. How Firms Capture Value From Their Innovations. J. Manag. 39 (5), 1123–1155.
Lakhani, K., Wolf, R.G., 2005. Why Hackers Do What They Do: Understanding Motivation and Effort in Free/Open Source Software Projects. In: Feller, J., FitzGerald, B., Hissam, S., Lakhani, K. (Eds.), Perspectives on Free and Open Source Software. MIT Press, Cambridge.
Lanjouw, J., Schankerman, M., 2001. Characteristics of Patent Litigation: A Window on Competition. RAND J. Econ. 32 (1), 129–151.
Laursen, K., Salter, A.J., 2014. The paradox of openness: Appropriability, external search and collaboration. Res. Policy 43 (5), 867–878.
Leiponen, A., Byma, J., 2009. If you cannot block, you better run: Small firms, co-operative innovation, and appropriation strategies. Res. Policy 38 (9), 1478–1488.
Levin, R.C., Klevorick, A.K., Nelson, R.R., Winter, S.G., 1987. Appropriating the from and Industrial Development. Brookings Paper on Economic Activity 18 (3), 783–831.
Manski, C.F., Lerman, S.R., 1977. The estimation of choice probabilities from choice based samples. Econometrica 45 (8), 1977–1988.
Moser, P., 2005. American economic association how do patent laws influence innovation ? Evidence from nineteenth-century world's fairs. Am. Econ. Rev. 95 (4), 1214–1236.
Moser, P., 2013. Patents and innovation: evidence from economic history. J. Econ. Perspect. 27 (1), 23–44.
Nambisan, S., Lyytinen, K., Song, M., 2017. Digital Innovation Management: Reinventing Innovation Management in a Digital World. MIS Quarterly 41 No. 1(March 2017) 223–238.
Ozalp, H., Cennamo, C., Gawer, A., 2018. Disruption in platform-based ecosystems. J. Manag. Stud. 55 (7), 1203–1241.
Parker, G., Alstyne, M.V., 2017. Innovation, openness, and platform control. Manag. Sci. 64 (7), 3015–3032.
Parker, G.G., Alstyne, M.V.W.V., 2005. Two-sided network effects: a theory of information product design. Manag. Sci. 51 (10), 1494–1504.
Parker, G.G., Van Alstyne, M.W., Choudary, S.P., 2016. Platform Revolution: How Networked Markets Are Transforming the Economyand How to Make Them Work for You. WW Norton & Company.
Png, I.P.L., 2017. Secrecy and Patents: Theory and Evidence from the Uniform Trade Secrets Act. Strategy Sci. 2 (3), 176–193.
Rochet, J., Tirole, J., 2006. Two-sided markets: a progress report. RAND J. Econ. 37 (3), 645–667.
Shapiro, C., Varian, H.R., 1998. Information rules: a strategic guide to the network economy. Harvard Business Press, Cambridge, MA.
Sundararajan, A., 2004. Managing digital piracy: Pricing and protection. Inform. Syst. Res. 15 (3), 287–308.
Teece, D.J., 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Res. Policy 15 (6), 285–305.
Tibshriani, R., 1996. Regression Shrinkage and Selection via the Lasso. Journal of the Royal Statistical Society. Series B (Methodological) 58 (1), 267–288.
Tiwana, A. (2004). Evolutionary Competition in Platform Ecosystems. Information Systems Research, 143(August 2016).
Tunca, T.I., Wu, Q., 2013. Fighting fire with fire: commercial piracy and the role of file sharing on copyright protection policy for digital goods. Inform. Syst. Res. 24 (2), 436–453.
Wen, W. and Zhu, F. (2017). Threat of Platform-Owner Entry and Complementor Responses: Evidence from the Mobile App Market. 1-42.
Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press, Cambidge, Mass.
Yin, B.P.-l., Davis, J.P., Muzyrya, Y., 2014. Entrepreneurial Innovation: Killer Apps in the iPhone Ecosystem. Am. Econ. Rev.: Papers and Procedings 104 (5), 255–259.
Yoo, Y., Henfridsson, O., Lyytinen, K., 2010. Research commentary: the new organizing logic of digital innovation: an agenda for information systems research. Inform. Syst. Res. 21 (4), 724–735.
Zhu, F., Iansiti, M., 2012. Entry into platform-based markets. Strategic Manag. J. 33 (1), 88–106.
Zhu, F., Liu, Q., 2018. Competing with complementors: An empirical look at Amazon.com. Strategic Manag. J. 39, 2618–2642.