PROTECTING THEIR DIGITAL ASSETS

Milan Miric, Kevin J. Boudreau & Lars Bo Jeppesen

Abstract

Innovation and product development by complementors on a digital platform differ in traditional and analog industries in ways that may influence the use of appropriability strategies—including the low costs of development, high uncertainty of outcomes, and the nature of digital technologies themselves. Taken together, these characteristics lead digital platforms to be populated predominantly by a "long tail" of very small firms. Here, we study the use of appropriability strategies (formal and informal) by third-party developers on a platform and consider whether smaller firms use such appropriability strategies differently from the larger firms that have typically been studied. In data on 809 developers on the Apple App Store representing 9,152 titles ("reweighed" to estimate population distributions), we find an overwhelming majority of firms attempt to protect their innovations (70%). Tiny firms—the vast majority of all developers-use only informal protections. Larger firms, in contrast, rely on formal intellectual property rights and use copyright, patents, and trademarks as commonly as do firms in traditional industries, but generally do so together with informal strategies. Several strategies distinct to digital platforms are documented. We interpret the uses of appropriability strategies in relation to digital competition faced by heterogenous innovators.

Keywords: *appropriability mechanisms, intellectual property, digital platforms, digital entrepreneurship.*

Miric: USC-Marshall School of Business (email: mmiric@marshall.usc.edu); Boudreau: Northeastern DMSB and National Bureau of Economic Research (e-mail: kevin@northeastern.edu); Jeppesen: Copenhagen Business School (email: lbj.ino@cbs.dk)

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 and bring them to market. While the importance for third-party developers on a platform to appropriate value has been established (Huang et al., 2012; Parker and Alstyne, 2017; Gawer and Henderson, 2007), existing studies of appropriability have focused primarily on larger firms in manufacturing industries (Cohen et al., 2000; Levin et al., 1987; Hall and Ziedonis, 2001) and have not addressed innovators on a platform, particularly the very small, entrepreneurial firms that populate many platforms. In this paper, we therefore seek to provide more insights into this understudied question of how innovators on a digital platform, particularly the very tiny firms that populate such platforms, protect and appropriate value from their innovations.

Digital platforms are technologies or technological intermediaries where the value of the technology depends on the availability of complementary technologies (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, or the value of a particular mobile application (app) platform (Android or iOS) depends on the availability of complementary apps. As a result, to build up their base of complementary products, many platforms owners have greatly reduced the costs of developing complementary innovations, allowing even very small firms or individuals to do so. This has led to platforms being populated by a "long tail" of a wide variety of developers, including hobbyists and amateurs who may not necessarily even pursue income-based payoffs. While these small-scale innovations may individually only account for relatively little revenue, together this long tail represents a considerable share of economic activity. In the case of the Apple App Store and Android Marketplace where third-party developers generate in excess of 130 Billion in revenues per year, the majority of developers are very small firms (often individuals), and they account for a considerable share of the revenue generated. There are numerous examples of platform marketplaces, such as the Unity asset store or the Salesforce app market where 3rd party developers generate billions of dollars in revenue from selling their products, and these are predominantly individual developers or very small firms. For these innovators, the ability to appropriate value and profit from their innovation is critical, because it directly relates to their decision to join the platform or undertake innovation (Huang et al., 2012; Parker and Alstyne, 2017; Gawer and Henderson, 2007). However, little is understood about how such small developers protect their innovations, including whether they rely on intellectual property rights (IPR) to protect their innovations the same way that larger firms do. For instance, there has been little exploration of how developers might protect their innovation when the expected gains from selling their products are lower than the costs of filing a patent. This is further complicated by the fact that property rights may not prove as effective in digital settings as they are in other industries (Graham et al., 2009).

The question of appropriability is critical to the study of innovation and innovation policy, as it helps policy makers to create conditions that 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). Gawer and Cusumano (2014) refer to this as "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 et al., 2010; Graham et al., 2009; Hall et al., 2017; Arundel et al., 1998; 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 et al., 2007; Hall et al., 2010) but this 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 explore 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 example of competing innovators working on a digital platforms today. Beyond its sheer economic magnitude, the Apple App Store presents an important context in which to study and document such strategies. First, it's products cover a wide range of digital market niches, such as productivity, gaming, education, finance. This allows us to study how innovation is protected around different swaths of platform production categories. Second, the Apple App Store permits us to capture the entire population of firms in this sector of the economy, including both large and small firms. This also means that we are able to study innovations created by very small entities, including autonomous developers, micro-enterprises, part-time developers, along with large companies. Third, the Apple App Store enforces US patent, copyright and trademark laws, which allows innovators to use these methods to protect their innovations. Additionally, the Apple App Store does not gain rights over the innovations that is released on its platform, which allows developers to use their IPR to protect their innovations.

We study the use of appropriability strategies identified by earlier studies (patents, copyrights, trademarks, lead time, and rapid innovation) as they are used by developers on the Apple App Store, and we consider whether smaller developers protect differently from larger developers. We are guided 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 safely estimate population-level patterns. Fortunately, the survey responses are themselves highly representative of the population, and multidimensional reweights do not substantially nor, statistically significantly differ from the unweighted results. We estimate the population-level incidence of the use of a range of appropriability mechanisms using the reweighed data.

We find that appropriability strategies on the Apple App Store cluster into those that use only informal protections (lead time and rapid innovation), and those that use a combination of formal (patents, copyrights and trademarks) and informal protections. 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. An important factor in determining whether firms use only informal protections or a combination of formal and informal protections is the size of the firm. We find that informal strategies, such as early entry and rapid innovation (versioning), are widely used by both large and small firms. However, we find that "formal" protections (patents, copyrights, and trademarks) are used generally by larger firms. Our results document that informal IPR protections are used by very small firms and part-time developers, while for large firms, formal IPR protections are important alongside the informal strategies even in these digital industries. Our results are robust to a number of potential controls, including the motivation of the developer, the revenue models, the firm attributes, the sources of the innovation, and the characteristics of the products. We utilize a variable selection model commonly used in machine learning applications that have been adapted to econometric applications (Double LASSO by Belloni et al., 2013 and Belloni et al., 2014) to identify which of these control variables may influence protection strategies, and we include them in our analysis.

Our study contributes to a vast literature on appropriability (Teece, 1986; Cohen et al., 2000; Levin et al., 1987) by taking a first step toward understanding the use of protection mechanisms in the new and increasingly important context of the digital platform. The digital nature of these platforms creates a set of conditions that differ fundamentally from the manufacturing and brick-and-mortar industries that have typically been studied (Greenstein et al., 2013; Goldfarb et al., 2015; Yoo et al., 2010; Nambisan et al., 2017). For instance, the ease of developing digital innovations and of copying and replicating digital innovations may greatly influence the ability of firms to appropriate value from their innovations. Similarly, the small scale of developers on these platforms, may shape the types of appropriability strategies being used, as other studies have found (Leiponen and Byma, 2009; Graham et al., 2009). In the spirit of earlier survey papers on appropriability (Cohen et al., 2000; Levin et al., 1987), we document the extent to which firms on a digital platform use different appropriability strategies and to which these strategies differ for smaller versus larger firms.

This is also an important contribution to the literature on platforms that has considered how third-party developers may protect themselves from the threat of the platform owner expropriating their innovations (Gawer and Henderson, 2007; Parker and Alstyne, 2017; Huang et al., 2012). We consider how innovators on the platform may appropriate value from innovation, under threat of competition from other developers as well. This contributes to our understanding of the number of different considerations that a platform owner must manage in creating conditions for third-party developers to have an incentive to join the platform. By understanding the appropriability strategies that are common on such platforms, the platform owner can create policies (such as IPR enforcement) to foster innovation on the platform.

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 in the economics of innovation.

The patent's role as a legal/formal protection mechanism has been prominent role 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. A number of 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 studied 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). There are studies that 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 is 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 less 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 varies 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 may want to protect those advantages by patenting their technology. Alternatively, a firm may patent part of it's technology while protecting another part through informal means (Levin et al., 1987). 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. A number of 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.

Above we have outlined 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 or Android market, that 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 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 "minimum viable product" and, in turn 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 API's 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).

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 or 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 and, in turn, have incentive 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 into a marketplace. In regulating and managing a platform, it is vital that it's ecosystem of third-party complementors be able to appropriate value from their innovations.

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 into 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 intensity with 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.

2.3 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 patents, registered copyright, or trademarks, or informal protections, such as rapid innovation, or lead-time advantages. These strategies are often characterized as formal and informal, because 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 lead-time advantages. We also expect that the use of formal and informal protections varies considerably across firms, and 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, and particularly with 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. This weighed against the relatively high cost of acquiring and enforcing IPR, 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 IPR (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. As a result, appropriability strategies may be used in combination , potentially combining formal and informal protection strategies. 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 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 such as lead-time or rapid innovation. However, to what extent informal strategies are used or the extent to which different appropriability strategies are used in combination are empirical questions.

3 Empirical Context

In the analysis to follow 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, there have been more than 2.4 million apps launched on the storefront, and developers have generated more than $70 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 covers 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.

There are a number of features that 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, ranging from productivity to gaming and internet services. As a result, the Apple App Store is broadly representative of digital innovators in the digital economy. 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 are compliant with US property rights. 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 from 2009 until 2014. This allowed us to obtain information about more than eight hundred thousand app developers (approximately thirty thousand of which provided email contact information). This observational information not only provided contact information but 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 by 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 twenty-four app categories. This is a relatively high number of respondents in relation to many surveys studies in management and social science and those studying appropriability strategies (Levin et al., 1987; Cohen et al., 2000; Graham et al., 2009). However, arguably the larger and more important point is that this sample size reflects only a small proportion (Approx.3%) of those invited to survey and a smaller proportion of the overall population of app developers (0.6%), again akin 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 not 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 do firms protect their intellectual assets". Doing so allows us to compare and contrast 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 latter 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 or 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 from 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 if 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 "made use of special technologies" as strategies to differentiate their products from competitors, respectively.[2]

Descriptive statistics for these variables are shown in Table 1.

TABLE 1: DESCRIPTIVE STATISTICS

[1]The use of patents, copyrights and trademarks follows what was surveyed in earlier studies. Early entry were often referred to as lead time advantages in the earlier surveys. Versioning is alogous to the "rapid" or "continous" innovation constructs used in earlier surveys. We adapted this to be versioning which 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.

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 by 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 response rate 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 and therefore our resulting analysis is biased (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 (or 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 Figure 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 (i.e., we cover the same range on the histogram).

FIGURE 1: COMPARISON OF SAMPLE AND DISTRIBUTION ACROSS OBSERVED VARIABLES

TABLE 2: COMPARISON OF SAMPLE AND POPULATION MEANS

The graphs in Figure 1 demonstrate that we have comparable coverage of our sample and population, in that we cover the spectrum of different product and developer characteristics. For instance, in terms of average product rating, our sample covers product ratings that range 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* suggest that we are over-sampling developers that release multiple titles and possibly larger companies. Similarly, our distribution of 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 construct sampling weights (as described above) to correct for our nonrandom sample and to ensure that our analysis is indicative of 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 Figure 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 Figure 2 show that patents and copyrights are infrequently used (13% and 23%, respectively), in comparison to other strategies, such as trademarks, versioning and lead-time (28%, 43%, and 48%, respectively). The use of patents is considerably less than what earlier studies on manufacturing settings have found (e.g., Cohen at al. 2000 find that 34.8% of firms use patents to protect their product innovations). Although, while 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 innovation. It is important to highlight that the numbers that we observe here for the use of informal strategies is comparable to what has been 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.

FIGURE 2: REPORTED USE OF DIFFERENT APPROPRIABILITY STRATEGIES (SAMPLE AND POPULATION)

4.2 Clustering of Formal and Informal strategies

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

Using principal component analysis, we find that there are two overall clusters of appropriability strategies: First, firms that use only informal (lead time and versioning) strategies and second, 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 if 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.

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

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 more than 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 are worried that this lack of variation may 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 a number of 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 its 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 into 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 a number of additional controls that may influence appropriability choices. For example, motivation to profit may influence the choice of how firms protect (Lakhani and Wolf, 2003; Harhoff et al., 2003) or the source of innovation may correlate with the need to protect (Laursen and Salter, 2014). While these 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 precision of our estimates, yet not account 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 traditional LASSO approach (Tibshriani, 1996) would result in an linear regression with a subset of the most statistically important variables; However this would also affect 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 generated by the LASSO, but it does not affect the parameters of the standard errors and coefficients (via

[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 and OSS 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 ($OBJECTIVE = RSS + \lambda \sum_{i=0}^{M} \mid w \mid$) where w is 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 coefficients. Therefore, the estimator reduces the size of 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 have the 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.

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.

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.

TABLE 3: RESULTS OF PROBIT REGRESSIONS FOR USE OF FORMAL/INFORMAL STRATEGIES

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 Protection, 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 Figure 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.

FIGURE 3: MARGINAL EFFECTS FOR FORMAL/INFORMAL PROBIT REGRESSIONS

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 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 as well as firms which do not use any protection. As the earlier cluster analysis suggests, firms that choose to protect generally do so through only informal means or a combination of formal and informal means.

TABLE 4: RESULTS OF MULTINOMIAL LOGIT REGRESSIONS FOR USE OF FORMAL & INFORMAL STRATEGIES

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 5. 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 protect 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, 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. Relatedly, 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, rather than not protecting 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 Figure 4. From the marginal effects, its clear that the use of formal strategies increases with firm size, both the use of formal strategies with informal strategies and formal strategies by themselves. 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 not likely to protect at all, while there is only a small share of larger firms that do not protect their innovations.

FIGURE 4: MARGINAL EFFECTS FOR MULTINOMIAL LOGIT REGRESSIONS

The control variables also suggest that protection strategies are correlated with a number of 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, 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 ttheir incidence with varying levels of firm size. In Figure 5, we present the marginal effects with respect to firm size. The individual regression results are shown in Appendix B.

FIGURE 5: MARGINAL EFFECTS FOR INDIVIDUAL PROBIT REGRESSIONS

The incidence of 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 infrequentlyAlternatively, 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 larger firms.

Additional Specifications and Robustness

We performed a number of 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 or the smaller subset of 626 firms for which we observe the full set of 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, 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 is only indicated by 11% of apps. These are companies that are not predominantly app developers but companies 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

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

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 separated from, a rapid expansion of research on the development of the digital 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 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 what is 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 typically disregarded, the results of the present study suggests 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 that has accounted for almost $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

[5]This is not shown in the tables, but is based on the fact that 42% of users 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.

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, in relation to the larger firms that have been typically studied. We provide evidence that appropriability strategies on the Apple App Store cluster into formal and informal protections. A large majority of firms (more than 70 percent) 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 by 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 comparison, Graham et al. (2009) find 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 a number of 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 other competitive pressures and appropriate value. The results of this paper help to inform the greater 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

[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).

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 in digital platforms populated by small companies. 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 inform the 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) and so it is 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 (Rochet and Tirole, 2015; Parker and Alstyne, 2005), 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 lead 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 they may design and enforce appropriate property rights.

From this perspective, understanding the importance of formal or informal property rights in allowing third-party developers to appropriate value may shape the policies that the platform chooses to undertake. From the perspective of a platform regulator (Gawer and Cusumano, 2014; Parker and Alstyne, 2005), 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

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

suggests that creating the ability of developers to enter 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. For instance, by 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.

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APPENDIX A: TABLES AND FIGURES

Figure 1: Comparison of Sample and Population across Observed Variables

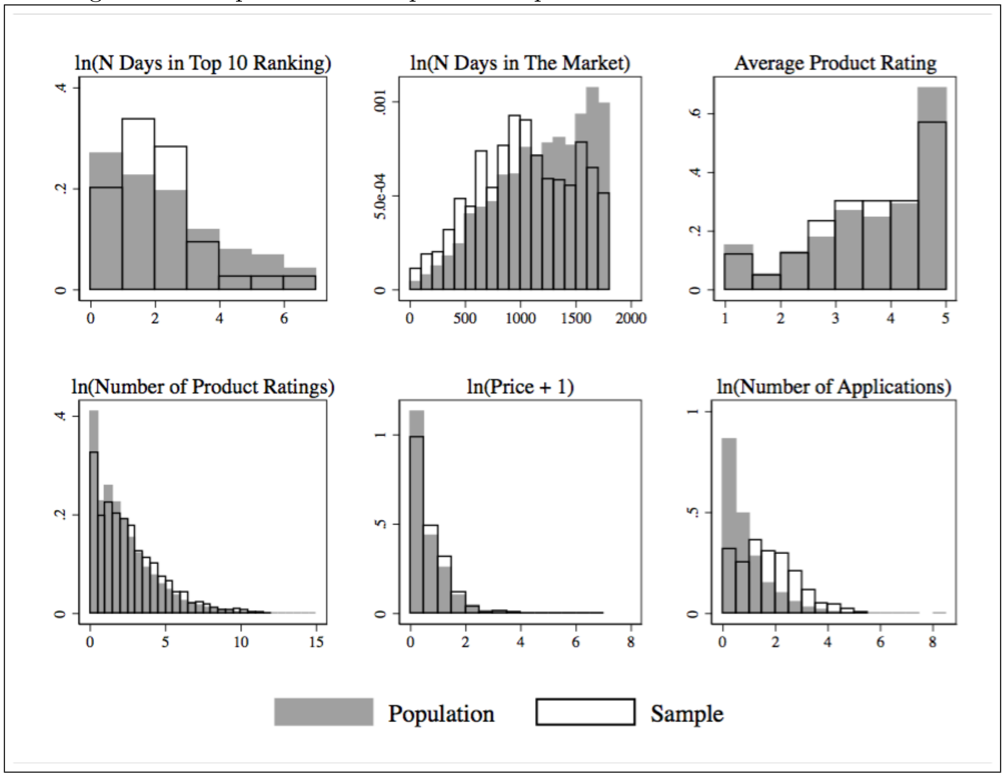


Figure 2: Reported Use of Different Appropriability Strategies (Sample & Population Estimate)

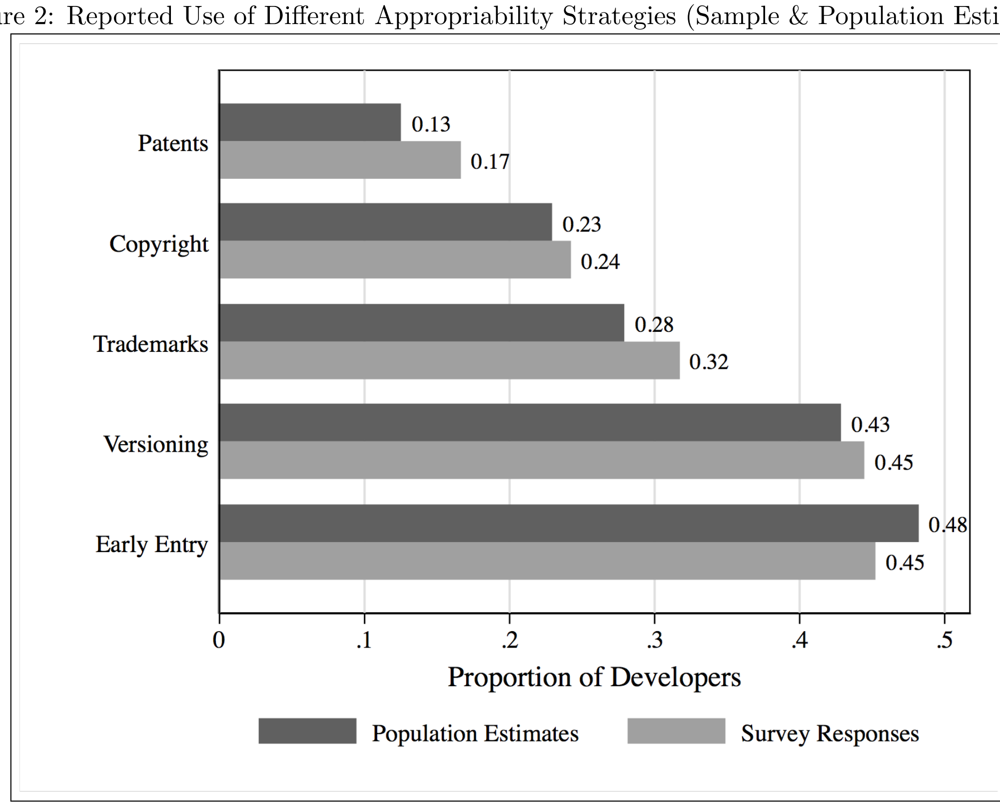


Figure 3: Marginal Effects for Incidence of Formal and Informal Strategies

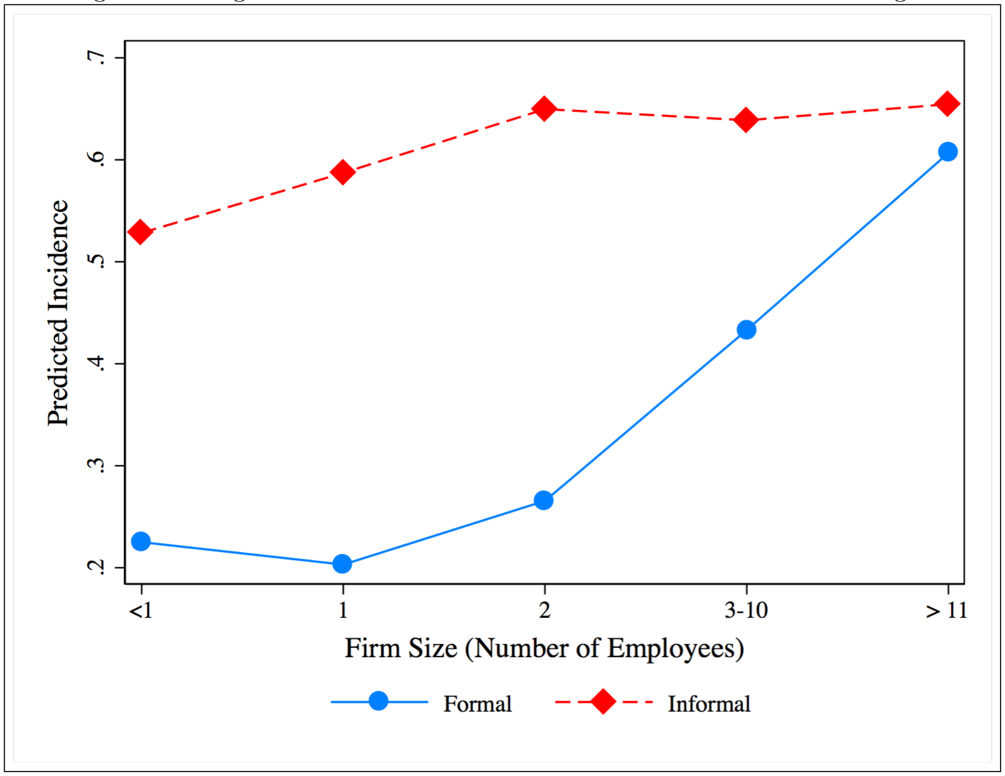


Figure 4: Marginal Effects for Multinomial Logit Regressions

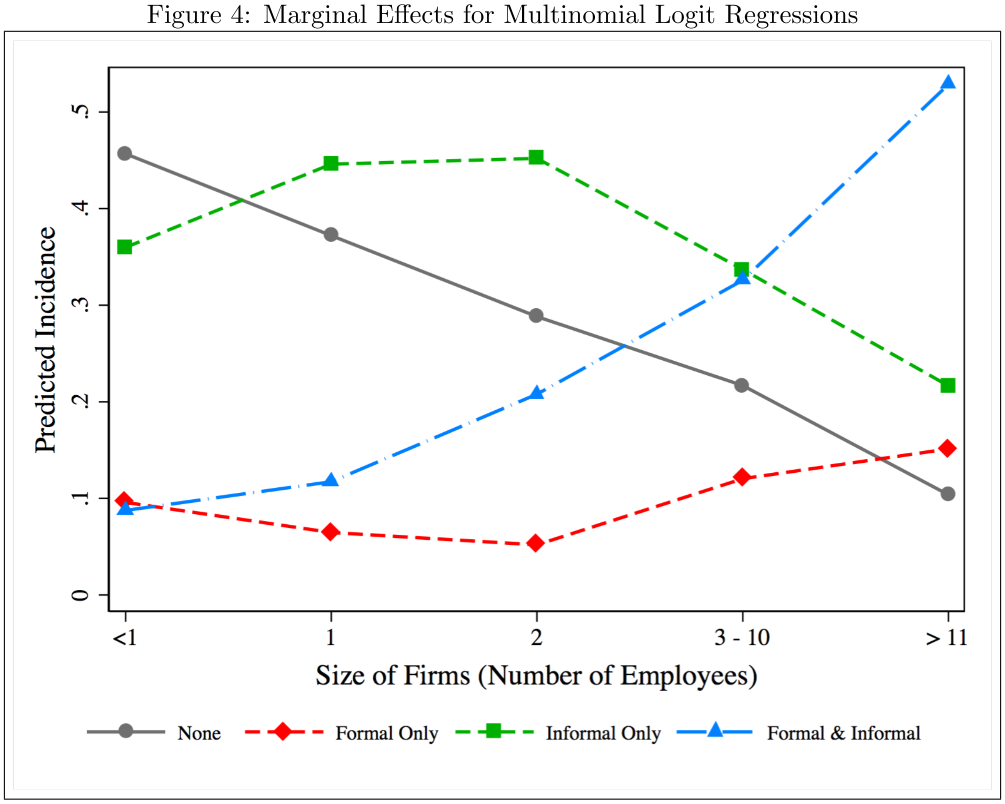


Figure 5: Marginal Effects for Multivariate Probit Regressions (Individual Protection Strategies)

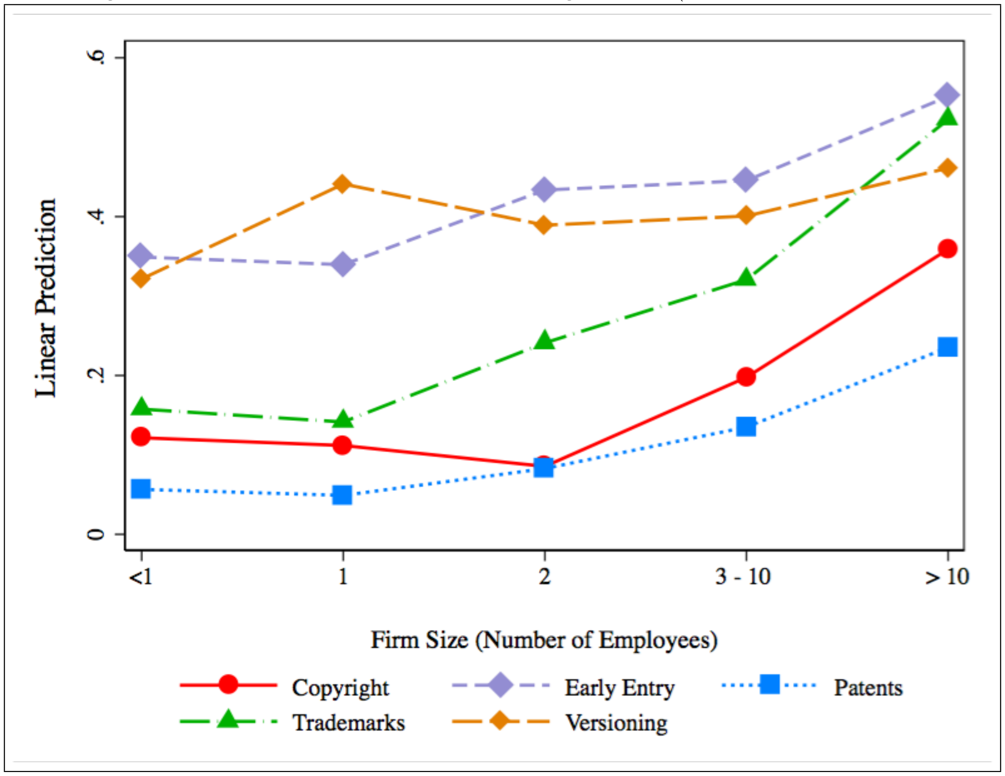


Table 1: Descriptive Statistics

	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						

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.

Table 3: Results of Multivariate Probit Regressions for Use of Formal & Informal Strategies
DV: *Indicator for FORMAL (Patents, Copyrights & Trademarks) and INFORMAL (Lead Time & Versioning).*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DV: Formal Protection				**DV: Informal Protection**			
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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Formal Protection				**Informal Protection**				**Formal & Informal Protection**			
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
Main 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. (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). $N = 626$.

APPENDIX B: SUPLEMENTARY ANALYSIS

Table B1. Results of Multivariate Probit Regressions for Use of Patents & Copyrights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DV: Patents				**DV: Copyright**			
Size: 1 Employee Firm	0.22	0.01	-0.11	-0.19	0.16	0.04	0.01	0.01
	(0.34)	(0.41)	(0.43)	(0.41)	(0.24)	(0.29)	(0.31)	(0.34)
Size: 2 Employee Firm	0.61	0.43	0.34	0.32	0.20	0.03	-0.12	-0.35
	(0.35)	(0.40)	(0.42)	(0.43)	(0.27)	(0.31)	(0.33)	(0.37)
Size: 3 Employee Firm	1.15***	0.92*	0.78*	0.85*	0.77***	0.69**	0.43	0.39
	(0.29)	(0.36)	(0.37)	(0.39)	(0.20)	(0.27)	(0.29)	(0.31)
Size: 4 Employee Firm	1.69***	1.38***	1.14**	0.95*	1.49***	1.42***	0.93**	0.91*
	(0.31)	(0.37)	(0.40)	(0.44)	(0.23)	(0.29)	(0.32)	(0.36)
Selected Control Variables								
Market Tenure		0.00	0.01	0.00		-0.00	-0.01	-0.01
		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)
Promotion Channel		0.34	0.23	0.40		0.47*	0.29	0.33
		(0.22)	(0.23)	(0.25)		(0.19)	(0.21)	(0.22)
USA Based		0.17	0.12	0.12		0.26	0.34*	0.35
		(0.16)	(0.18)	(0.17)		(0.14)	(0.15)	(0.18)
Hobbyist Motivation		-0.47	-0.55	-0.37		-0.28	-0.27	-0.18
		(0.58)	(0.62)	(0.58)		(0.36)	(0.40)	(0.42)
Licensing		0.46*	0.29	0.33		-0.09	-0.28	-0.24
		(0.21)	(0.22)	(0.24)		(0.21)	(0.22)	(0.26)
App Revenue		-0.24	-0.26	-0.39		0.03	-0.05	-0.14
		(0.18)	(0.20)	(0.21)		(0.16)	(0.18)	(0.21)
Diff: Network Effects			0.08	0.02			0.22	0.62**
			(0.22)	(0.22)			(0.19)	(0.24)
Diff: Social			0.09	-0.02			0.38*	0.12
			(0.21)	(0.25)			(0.19)	(0.23)
Source: Industry Trends			0.41*	0.35			0.27	0.23
			(0.18)	(0.19)			(0.16)	(0.18)
Motivation: New Skills			-0.07	-0.06			-0.34*	-0.56**
			(0.18)	(0.18)			(0.15)	(0.17)
Diff: HigherQuality			-0.13	0.06			-0.07	0.12
			(0.18)	(0.20)			(0.15)	(0.16)
Source: Users			0.11	0.07			-0.12	-0.23
			(0.18)	(0.18)			(0.15)	(0.18)
Source: Market Research			0.13	0.02			0.36*	0.26
			(0.18)	(0.22)			(0.15)	(0.18)
Diff: Design Artwork			-0.21	-0.10			0.10	0.27
			(0.18)	(0.20)			(0.17)	(0.18)
Diff: Special Tech			0.14	0.12			0.13	0.16
			(0.21)	(0.21)			(0.19)	(0.23)
Motivation: Income			0.13	0.13			0.16	0.13
			(0.20)	(0.21)			(0.17)	(0.20)
Motivation: See Others Using			-0.26	-0.16			-0.12	-0.07
			(0.18)	(0.21)			(0.15)	(0.17)
Motivation: Fun			0.17	-0.16			0.13	0.04
			(0.19)	(0.18)			(0.16)	(0.19)
Categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.06***	-2.02***	-1.96***	-1.83***	-1.49***	-1.46***	-1.46***	-1.20**
	(0.27)	(0.41)	(0.43)	(0.52)	(0.18)	(0.31)	(0.33)	(0.41)
χ^2	245.79	297.85	464.46	1667.35	245.79	297.85	464.46	1667.35
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ll	-1436.00	-1403.50	-1291.64	-995.16	-1436.00	-1403.50	-1291.64	-995.16

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B2. Results of Multivariate Probit Regressions for Use of Trademarks

	(1)	(2)	(3)	(4)
	DV: Trademark			
Size: 1 Employee Firm	0.22	-0.05	-0.03	-0.01
	(0.20)	(0.25)	(0.27)	(0.29)
Size: 2 Employee Firm	0.67**	0.43	0.40	0.60
	(0.22)	(0.26)	(0.28)	(0.32)
Size: 3 Employee Firm	0.95***	0.76**	0.65**	0.92***
	(0.19)	(0.24)	(0.25)	(0.28)
Size: 4 Employee Firm	1.59***	1.40***	1.22***	1.26***
	(0.21)	(0.26)	(0.29)	(0.33)
Selected Control Variables				
Market Tenure		0.01	0.01	0.01
		(0.00)	(0.00)	(0.01)
Promotion Channel		0.44*	0.40*	0.53*
		(0.18)	(0.19)	(0.23)
USA Based		0.34**	0.38**	0.45**
		(0.13)	(0.13)	(0.15)
Hobbyist Motivation		-0.57	-0.34	-0.24
		(0.34)	(0.36)	(0.38)
Licensing		0.30	0.24	0.31
		(0.19)	(0.19)	(0.23)
App Revenue		0.02	-0.09	-0.40*
		(0.15)	(0.16)	(0.18)
Diff: Network Effects			0.44**	0.52**
			(0.17)	(0.18)
Diff: Social			0.06	0.01
			(0.17)	(0.18)
Source: Industry Trends			0.10	-0.03
			(0.14)	(0.16)
Motivation: New Skills			-0.34*	-0.31
			(0.13)	(0.16)
Diff: HigherQuality			0.04	0.09
			(0.14)	(0.16)
Source: Users			0.11	0.25
			(0.13)	(0.16)
Source: Market Research			-0.08	-0.04
			(0.14)	(0.17)
Diff: Design Artwork			0.11	0.25
			(0.14)	(0.16)
Diff: Special Tech			-0.17	-0.05
			(0.17)	(0.18)
Motivation: Income			0.22	0.43**
			(0.15)	(0.16)
Motivation: See Others Using			-0.06	-0.06
			(0.13)	(0.15)
Motivation: Fun			-0.01	-0.09
			(0.14)	(0.16)
Categories	Yes	Yes	Yes	Yes
Constant	-1.29***	-1.48***	-1.52***	-1.83***
	(0.16)	(0.28)	(0.31)	(0.37)
χ^2	245.79	297.85	464.46	1667.35
p	0.00	0.00	0.00	0.00
ll	-1436.00	-1403.50	-1291.64	-995.16

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B3. Results of Multivariate Probit Regressions for Use of Early Entry and Versioning

	(1)	(2)	(3)	(4)	(15)	(6)	(7)	(8)
	DV: Early Entry				**DV: Versioning**			
Size: 1 Employee Firm	0.14	0.27	0.01	0.09	0.42*	0.46*	0.37	0.48
	(0.16)	(0.22)	(0.23)	(0.25)	(0.17)	(0.22)	(0.23)	(0.27)
Size: 2 Employee Firm	0.41*	0.58*	0.29	0.36	0.42*	0.49*	0.27	-0.11
	(0.19)	(0.23)	(0.25)	(0.28)	(0.19)	(0.24)	(0.25)	(0.30)
Size: 3 Employee Firm	0.47**	0.62**	0.32	0.45	0.47**	0.56**	0.29	0.18
	(0.15)	(0.21)	(0.23)	(0.25)	(0.16)	(0.21)	(0.23)	(0.27)
Size: 4 Employee Firm	0.83***	0.95***	0.69*	0.74*	0.80***	1.01***	0.47	0.26
	(0.19)	(0.24)	(0.27)	(0.30)	(0.19)	(0.25)	(0.27)	(0.34)
Selected Control Variables								
Market Tenure		0.01*	0.01	0.00		0.00	0.00	-0.01
		(0.00)	(0.00)	(0.01)		(0.00)	(0.00)	(0.01)
Promotion Channel		0.09	0.00	-0.13		-0.09	-0.14	-0.01
		(0.17)	(0.19)	(0.22)		(0.18)	(0.19)	(0.25)
USA Based		0.17	0.12	0.15		-0.01	-0.03	-0.08
		(0.11)	(0.12)	(0.14)		(0.11)	(0.12)	(0.14)
Hobbyist Motivation		0.29	0.11	0.06		0.18	0.33	0.21
		(0.25)	(0.27)	(0.28)		(0.25)	(0.28)	(0.31)
Licensing		0.42*	0.22	0.06		0.21	0.06	-0.11
		(0.18)	(0.20)	(0.25)		(0.18)	(0.19)	(0.24)
App Revenue		0.00	-0.18	-0.35*		0.47***	0.29	0.14
		(0.13)	(0.15)	(0.18)		(0.14)	(0.15)	(0.18)
Diff: Network Effects			0.09	0.16			0.49**	0.48*
			(0.17)	(0.22)			(0.16)	(0.19)
Diff: Social			0.28	0.21			0.25	0.15
			(0.16)	(0.21)			(0.15)	(0.20)
Source: Industry Trends			0.15	-0.03			0.14	0.10
			(0.13)	(0.15)			(0.13)	(0.16)
Motivation: New Skills			-0.10	-0.11			-0.14	-0.23
			(0.13)	(0.16)			(0.12)	(0.15)
Diff: HigherQuality			0.09	0.14			0.53***	0.63***
			(0.13)	(0.15)			(0.13)	(0.14)
Source: Users			-0.08	0.10			0.26*	0.24
			(0.12)	(0.14)			(0.12)	(0.14)
Source: Market Research			0.15	0.20			0.14	0.24
			(0.13)	(0.15)			(0.13)	(0.15)
Diff: Design Artwork			-0.03	0.03			0.25	0.25
			(0.13)	(0.14)			(0.13)	(0.15)
Diff: Special Tech			0.98***	0.96***			-0.17	-0.16
			(0.17)	(0.20)			(0.16)	(0.19)
Motivation: Income			0.24	0.22			0.06	0.10
			(0.14)	(0.17)			(0.14)	(0.15)
Motivation: See Others Using			0.55***	0.54***			0.06	-0.01
			(0.13)	(0.15)			(0.12)	(0.14)
Motivation: Fun			0.38**	0.40*			-0.14	-0.01
			(0.13)	(0.16)			(0.13)	(0.15)
Categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.60***	-1.15***	-1.68***	-1.39***	-0.79***	-1.31***	-1.69***	-1.27***
	(0.12)	(0.25)	(0.29)	(0.31)	(0.13)	(0.26)	(0.29)	(0.35)
χ^2	245.79	297.85	464.46	1667.35	245.79	297.85	464.46	1667.35
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ll	-1436.00	-1403.50	-1291.64	-995.16	-1436.00	-1403.50	-1291.64	-995.16

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B4. Results of Principle Component Analysis

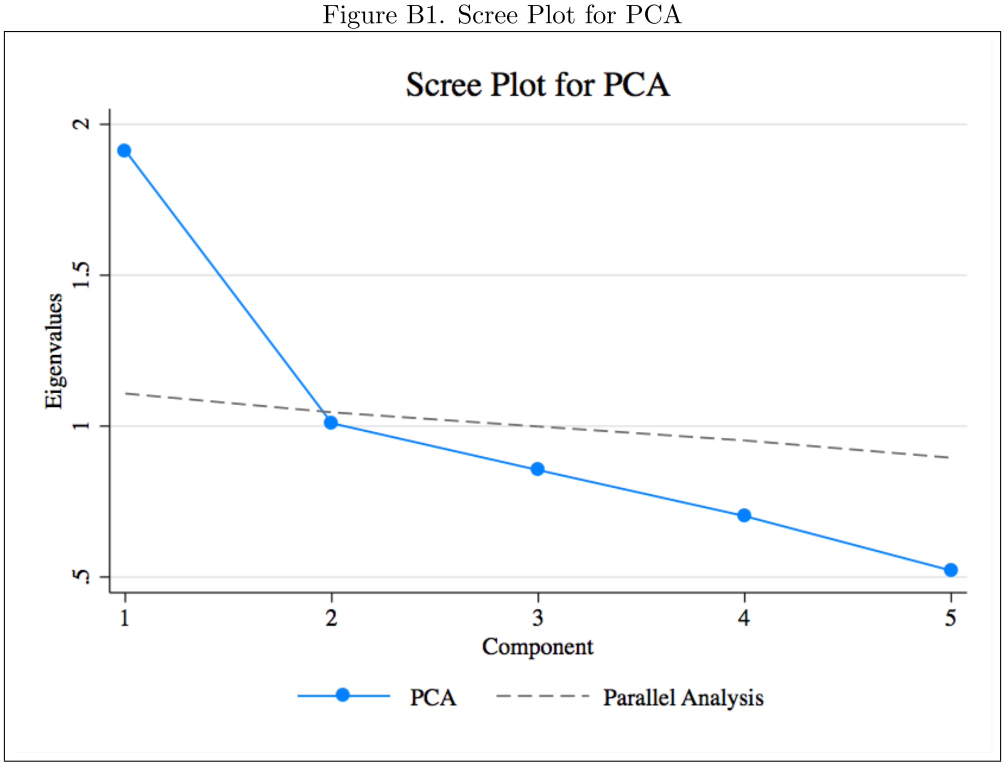
Part A. Explained Variance by Components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative
1	1.91	0.38	0.01	0.38
2	1.01	0.20	0.01	0.58
3	0.85	0.17	0.01	0.76
4	0.70	0.14	0.01	0.90
5	0.52	0.10	0.01	1.00

Part B. Principal components/correlation

	Coefficient	St. E.	z	P> |z|
Component 1				
Patents	0.48	0.03	14.35	0.00
Copyright	0.55	0.03	19.63	0.00
Trademarks	0.55	0.03	19.60	0.00
Early_Entry	0.30	0.05	6.23	0.00
Versioning	0.26	0.05	5.12	0.00
Component 2				
Patents	(0.23)	0.09	(2.52)	0.01
Copyright	(0.17)	0.08	(2.16)	0.03
Trademarks	(0.28)	0.06	(4.52)	0.00
Early_Entry	0.57	0.18	3.24	0.00
Versioning	0.72	0.14	4.96	0.00
Component 3				
Patents	0.02	0.17	0.09	0.93
Copyright	(0.18)	0.11	(1.56)	0.12
Trademarks	0.04	0.11	0.39	0.70
Early_Entry	0.76	0.13	5.78	0.00
Versioning	(0.62)	0.17	(3.76)	0.00
Component 4				
Patents	0.83	0.03	24.55	0.00
Copyright	(0.46)	0.10	(4.80)	0.00
Trademarks	(0.30)	0.10	(2.95)	0.00
Early_Entry	(0.04)	0.16	(0.25)	0.80
Versioning	0.08	0.14	0.55	0.58
Component 5				
Patents	(0.12)	0.11	(1.09)	0.28
Copyright	(0.66)	0.06	(10.49)	0.00
Trademarks	0.73	0.04	16.51	0.00
Early_Entry	(0.07)	0.07	(1.05)	0.29
Versioning	0.14	0.06	2.22	0.03

Figure B1. Scree Plot for PCA



APPENDIX C: SURVEY INSTRUMENT

Thank you for supporting this innovation research across a consortium of universities! After finishing, just indicate whether you'd like the report and choice of charity.

Name of your mobile app company or project:

Please re-write the company or project name here, if the above is incorrect or missing:

Country — Select Country

City

---

1. How large is the mobile app venture?

- ○ Fewer than 1 full-time person
- ○ 1 person
- ○ 2 people
- ○ 3 - 10 people
- ○ 11 - 50 people
- ○ 50+ people

---

2. What is your business model? How do you try to make money?

- ☐ we don't try to make money from our apps
- ☐ donations
- ☐ charge for developing for outside clients
- ☐ app is just a channel, promotion for something else
- ☐ advertising revenue
- ☐ premium version of the app is not free
- ☐ charge for the sale of the app, itself
- ☐ charge other companies to license the software
- ☐ 'in app' charges to sell added features or functions
- ☐ create software used by other software companies in their products

- [ ] Other

3. Have you used any of the following?

- [ ] registered trademarks
- [ ] registered copyrights
- [ ] patents
- [ ] formal non-disclosure agreements (NDAs)
- [ ] formal end-user agreement (EULAs)
- [ ] digital rights management(DRM)

4. Has your mobile app venture done any of the following? Check any that apply.

- [ ] deliberately designed your app software to be hard to copy, complex
- [ ] revealed mobile app source code
- [ ] stipulated that intellectual property created by employees during employment will be owned by the venture
- [ ] placed app code under open source license
- [ ] used employee non-compete agreements

5. Where do your app ideas come from? Check any that apply.

- [ ] app users
- [ ] we simply think them up
- [ ] scan other industries
- [ ] friends, family, acquaintances
- [ ] exploit web analytics
- [ ] we buy or license software from other developers
- [ ] university research
- [ ] market research
- [ ] other
- [ ] keep ahead of industry trends

6. Do you believe any of these are a concern?

	This is a concern (1)	This is an important concern (2)
consumer piracy & sharing	○	○
platform OS vendors use mobile app ideas	○	○
developers re-use ideas from other apps	○	○

third parties claiming infringement	○	○

7. Would the venture be more inclined to discourage or encourage other mobile developers to use your ideas and code?

discourage re-use (1)	(2)	(3)	(4)	encourage re-use (5)
○	○	○	○	○

8. For the types of apps you make, how easy do you think it is for mobile app developers to copy?

	Very Easy (1)	(2)	(3)	(4)	Very Difficult (5)
basic idea for app	○	○	○	○	○
underlying source code	○	○	○	○	○

9. How tough is the competition in the categories of apps you make?

not much competition (1)	(2)	(3)	(4)	very tough competition (5)
○	○	○	○	○

10. What is your personal motivation for getting involved in mobile apps?

- ☐ to make an income
- ☐ to learn new skills
- ☐ to see other people using my app creations
- ☐ to do especially challenging things
- ☐ to be an entrepreneur
- ☐ to be part of an exciting industry
- ☐ to use the app myself
- ☐ for fun!
- ☐ to increase my job/career prospects
- ☐ to be part of the app developer community
- ☐ to be creative, to create new things
- ☐ it´s a hobby or personal interest outside my main job
- ☐ to meet other interesting people
- ☐ to tackle especially interesting technical / development problems
- ☐ to build my reputation
- ☐ maybe I´ll get rich!

11. What are the overall goals of your mobile app company or project?

- ◯ maximize economic value
- ◯ other, please specify: ______

12. Do you do any of the following to try to differentiate your apps(s)?

- ☐ we don't really try to differentiate our app
- ☐ through artwork, design, interface, layout
- ☐ building "network effects" around a large base of users
- ☐ building social interactions among users
- ☐ regularly upgrading or creating new versions
- ☐ offering a different kinds of apps than what is offered by other developers
- ☐ offering higher quality apps than what is offered by other developers
- ☐ targeting specific users
- ☐ better marketing and promotion of the app
- ☐ pioneering new types of apps
- ☐ entering early into the market
- ☐ using special technologies (ex: speech, LBS, AR, etc)
- ☐ providing better artistry, narratives or characters
- ☐ providing specialized content or media
- ☐ allowing user-generated content
- ☐ other ______

Thank you for your input, and finally can we make a donation on your behalf?

- ○ International Committee of the Red Cross
- ○ Doctors Without Borders
- ○ One Laptop per Child
- ○ UNICEF Education Programs
- ○ WWF (World Wildlife Fund)

Would you like a report of our analysis?

- ☐ Yes

What email would you like the survey report delivered to?

What is your personal role or position in your mobile app company or project?

Submit

APPENDIX D: FORMAL MODEL OF CHOICE OF APPROPRIABILITY MECHANISM

Here we develop a model of the decision of a firm to use an appropriability strategy.[1]

Consider an app developer that is creating a product with a expected market value of v. In addition to the costs of development (which we assume to be fixed), the firm can choose to invest in using an appropriability strategy so that they can limit competition and increase their post-innovation rents. Let i indicate the choice of appropriability strategy from the set of potential strategies identified by previous studies: Patents, Copyrights, Trademarks, Lead Time and Rapid Innovation.

Let α denote the probability of successfully implementing protection strategy i with quadratic cost $c\alpha^2/2$. The costs of implementing these strategies are not fixed. For instance, an innovation may acquire multiple patents and "thicket" an area around their innovation to ensure that they exclude competitors. If the protection strategy is successfully implemented, than the developer is effectively a 'local' monopolist and can expect to gain a payoff of $v(1-\lambda_i)$, otherwise the payoff is $v(1-\lambda_0)$ where λ_0 and λ_1 is the probability that a competitor will enter compete a-la-bertrand reducing the payoff to zero, in the case that the firms protect and do not protect respectively. The relative difference between λ_0 and λ_1 reflects the relative effectiveness of the IPR strategy.

The resulting payoff function for the firm is

$$\pi = \alpha(1-\lambda_i)v + v(1-\alpha)(1-\lambda_0) - c\alpha^2/2 \tag{1}$$

Solving for the optimal level of investments in equilibrium, yields $\alpha^* = v(\lambda_0 - \lambda_1)/c$. Even this simple result provides insight into the factors that shape the probability that a firm will utilize appropriability strategies.

Proposition 1. *The probability of implementing a protection strategy increases with the baseline threat of competition (λ_0) and the value of the innovation (v), and decreases with the cost of implementing the strategy (c).*[2]

There are several results that emerge from this very simple result. Expectedly, as the value of an innovation increases the probability that a developer will protect their innovation increases. However, if the value of the technology is low they may choose to not protect at all ($\alpha \approx 0$). Even if $\lambda = 1$, meaning the cost of

[1]We draw inspiration from Aghion, Howitt and Prantl (2013) - *Revisiting the Relationship Between Competition, Patenting, and Innovation* which provides a versatile setup for the relationship between IP rights and investment. This is approach is general enough that we can model diverse strategies such as patenting, rapid innovation or early entry within the same framework.

[2]The proof for this is straightforward since $\partial\alpha/\partial\lambda_0 \geq 0$, and $\partial\alpha/\partial v \geq 0$, $\partial\alpha/\partial c \leq 0$.

protecting may several orders of magnitude be more than v, which in turn means that the probability that a firm protect is quite low (For instance, with costly patents and a low value product).

If we considered that developers may choose from multiple protection strategies, then we may expect that a developer will choose the least costly protection strategy first. However, we may imagine that once a developer implements a lower cost protection strategy, they may want to implement an additional more costly strategy. This could be extended where λ_0 would be the threat of competition under the low cost strategy, and λ_1 would be the threat of competition under the higher cost strategy.

Given that informal strategies are less costly than formal strategies, this would imply that informal strategies will be the first choice for protecting all innovations. However, for more valuable innovations (such as those created by larger firms), it may be feasible to use both formal protections, on top of informal protections to protect their innovation. This is consistent with the arguments in Section 2.3.