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Slack Time and Innovation

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Abstract. The relationship between slack resources and innovation is complex, with the literature linking slack to both breakthrough innovations and resource misallocation. We reconcile these conflicting views by focusing on a novel mechanism: the role slack time plays in the endogenous allocation of time and effort to innovative projects. We develop a theoretical model that distinguishes between periods of high- (work weeks) versus low- (break weeks) opportunity costs of time. Low-opportunity cost time during break weeks may induce (1) lower quality ideas to be developed (a selection effect); (2) more effort to be applied for any given idea quality (an effort effect); and (3) an increase in the use of teams because scheduling is less constrained (a coordination effect). As a result, the effect of an increase in slack time on innovative outcomes is ambiguous, because the selection effect may induce more low-quality ideas, whereas the effort and coordination effect may lead to more high-quality, complex ideas. We test this framework using data on college breaks and on 165,410 Kickstarter projects across the United States. Consistent with our predictions, during university breaks, more projects are posted in the focal regions, and the increase is largest for projects of either very high or very low quality. Furthermore, projects posted during breaks are more complex, and involve larger teams with diverse skills. We discuss the implications for the design of policies on slack time.

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Keywords: crowdfunding • entrepreneurship • slack time • low-opportunity cost time • teamwork • internet

It’s no coincidence that Microsoft and Facebook both got started in January. At Harvard that is (or was) Reading Period, when students have no classes to attend because they’re supposed to be studying for finals.

—Paul Graham, Y Combinator Founder, quoted in “How to Get Startup Ideas”

1. Introduction

The relationship between slack resources and innovation is complex, with the literature linking slack resources to breakthrough innovations and increased experimentation (Cyert and March 1963, Thompson 1967, Bourgeois 1981, Levinthal and March 1981), but also to individuals and teams becoming less selective and disciplined about the projects they work on (Cyert and March 1963, Leibenstein 1969, Fama 1980, Staw et al. 1981, Jensen 1986, Jensen et al. 1994). This poses a challenge for organizations that want to encourage innovation to

increase their productivity and competitiveness and also worry that introducing slack may negatively distort the allocation of time and effort across the organization.

We build on this tension, but identify a novel driver for the effects observed in the literature by focusing on how slack time shapes the allocation of resources to innovative projects. In particular, using a simple economic framework, we capture how differences between periods of high- (work weeks) versus low- (break weeks) opportunity costs of time influence the quantity, quality, and type of projects innovators work on. In the setup, low-opportunity cost time during breaks may induce (1) lower quality ideas to be developed (a selection effect); (2) more effort to be applied for any given idea quality (an effort effect); and (3) an increase in the use of teams because scheduling is less constrained (a coordination

effect). As a result, the effect of slack time on inventive outcomes is ambiguous because on the one hand the selection effect may induce lower quality ideas to be developed, but, on the other hand, the effort and coordination effects may lead to more high-quality, complex ideas.

We take the predictions of the framework to data from Kickstarter, the world's leading reward-based crowdfunding website.¹ Crowdfunding platforms have become increasingly important for entrepreneurial endeavors in a variety of segments, ranging from the arts to technology (Agrawal et al. 2013, Belleflamme et al. 2014, Mollick and Nanda 2016).² Understanding the determinants of the creative supply on these platforms is in and of itself interesting. Additionally, the results provide novel insights for the design of "slack time" policies within organizations.

In the empirics, we leverage variation in the availability of slack time generated by school breaks across locations with top U.S. universities. Relative to more fragmented, constrained time during the semester, breaks provide students with continuous blocks of time to work on nonschool related projects. The sample includes all projects launched on Kickstarter between April 2009 and April 2015, and information on the exact timing of school breaks across regions. The unit of analysis is the city-week, and we compare the number and the characteristics of projects launched in a given city during break weeks versus work weeks. The regressions control for city and week fixed effects to isolate confounding factors such as general time trends, seasonality, and different baseline levels of innovative activity across locations. Even though we do not observe the exact amount of time creators spend on their projects, we take advantage of fine-grained data on project characteristics, market valuation, and proxies for the amount of effort spent on the fundraising pages to capture inventive inputs and outputs. The combination of the large-scale nature of the data, which cover 165,410 projects and 7 years of observations, and a novel identification strategy lets us cleanly estimate the causal effect of changes in slack time on innovative outcomes.

First, we document the positive impact of slack time on the quantity of projects launched. The regression results show that during school breaks the number of crowdfunding campaigns created increases by up to 45%. We provide a series of results in support of the causal interpretation that these additional projects are driven by an increase in the availability of slack time. Specifically, we show that when top engineering schools are on break, we see a positive effect on technology projects but not on art projects and vice versa when art and design schools are on break. We then examine days when universities are closed for snow, providing an exogenous increase in slack time:

significantly more projects are posted on snow days. As further robustness, we show that the increase in projects is unlikely to be driven by increased capital availability due to students providing more funds to projects while on break.

Second, relative to work weeks, break weeks are associated with significantly more projects at the very low end of the value distribution, fewer projects in the middle, and more projects at the high end of the distribution. The empirical patterns also support the predictions about differences in effort and coordination costs. When the opportunity cost of time is lower, more effort is allocated to ideas, especially high-value ones. Furthermore, "overlapping" slack is disproportionately beneficial for the creation of complex projects that may require input and coordination between team members with different skills and perspectives.

Third, we exploit a policy change on the platform, which affects only two of its categories, to investigate if policies targeted at curtailing low-quality contributions can mitigate the negative effects of slack on innovation. Using a difference-in-differences empirical strategy, we find that after the shock the relative shares of top-value and team projects in the affected categories increase disproportionately during breaks, suggesting that the new rules were effective in limiting resource misallocation.

The paper provides a novel framework—centered on the opportunity cost of an innovator's time—for analyzing the relationship between slack time and innovative outputs. The results highlight that a sufficient amount of time (in contiguous blocks, in particular) is critical for implementing high-potential and complex projects, and that "overlapping slack" is important when ideas benefit from teams with diverse skills. This is consistent with recent shifts from spread-out forms of individual slack time (e.g., Google's 20% time) to more structured programs that provide teams of employees with longer, continuous blocks of time off from regular commitments (e.g., Google's "Area 120"). The findings also caution that too many marginal, low-potential projects are generated when slack time is available. Therefore, complementary policies, such as the stricter screening mechanism we study with the policy change on the platform, are likely to be valuable in conjunction with slack.

The paper proceeds as follows. Section 2 summarizes the literature on slack and innovation. Section 3 presents a formal model that derives the differences in the quantity and type of projects developed during periods of high- versus low-opportunity cost of time. Section 4 describes the data and empirical strategy. Section 5 reports the regression results, and Section 6 concludes.

2. The Literature on Slack and Innovation

Innovation requires organizations and individuals to allocate time and resources away from short-run objectives, and to focus attention not only on long-run goals but also on less explored areas of the search space. “Slack search” (March 1976, Levinthal and March 1981) fundamentally differs from “problemistic search” (Greve 2003) because of the way it relaxes the constraints that normally guard the use of key resources within an organization (Bourgeois 1981). Acting as a catalyst for exploration, slack allows firms to experiment with new ideas, products, strategies and markets that would otherwise be considered too risky to engage in under a traditional cost-benefit analysis (Thompson 1967, Hambrick and Snow 1977, Moses 1992). Slack also contributes to the long-term growth of an organization by buffering it from changes in the environment (Galbraith 1973, Meyer 1982) and their repercussions on performance (Kamin and Ronen 1978); by isolating it from the internal turbulence generated by the often conflicting incentives of its subunits (Cyert and March 1963, Pondy 1967); by helping it cope with task uncertainty in decision making and information processing (Galbraith 1973); and by allowing it to initiate the changes in strategy and policies (Bourgeois and Singh 1983) needed for adaptation (Kraatz and Zajac 2001). Furthermore, in the presence of slack, failure of an innovative project is less likely to lead to a loss in legitimacy within the market and to consequences for the managers involved, as downside risk can be absorbed by the organization without constituting a threat to its long-run survival (Thompson 1965). Whenever internal capital market controls on R&D are less stringent and “patient capital” is available, individuals can champion high variance projects that have an extremely high chance of failure, but that can also deliver—if successful—very high returns (Astley 1978, Mokyr 1990, Garud and Van de Ven 2002). Whereas empirically this often translates into slack being associated with superior performance, risk-taking, and innovation (Singh 1986, Bromiley 1991, Miller and Leiblein 1996), the relationship has been shown to both depend on the underlying quality of the organizations involved (Greenley and Oktemgil 1998) and on the overall level of slack available (Nohria and Gulati 1996).

In their seminal piece, Cyert and March (1963) highlight how, in the presence of slack, negotiations and innovation can also be less effective, as resource abundance leads individuals to be less selective and apply less effort. Similarly, agency theory identifies slack as a source of conflict between the objectives of the principal and the actions of the agent, and concludes that the buffer that slack provides diminishes risk-taking behavior, is a source of inefficiency, and leads to inferior performance (Leibenstein 1969,

Fama 1980, Jensen 1986, Jensen et al. 1994). Under this view, slack encourages rent-seeking, decreases exploration (Tan and Peng 2003, Mishina et al. 2004), makes it easier for individuals to find support for their pet projects, and more difficult for organizations to abandon bad projects (Staw et al. 1981). As a result, organizations that are resource constrained can outperform those with slack because of the more disciplined nature of their decisions (Starr and MacMillan 1990, Mosakowski 2002, Baker and Nelson 2005).

A first set of attempts at reconciling these opposing views on slack (Singh 1986, Sharfman et al. 1988, Tan and Peng 2003) builds on Bourgeois’ (1981) insight that not all forms of slack resources are the same, and vary in their degree of liquidity, that is, in how difficult it is to repurpose them toward new uses. While “unabsorbed,” uncommitted slack is mostly beneficial, absorbed slack can be harmful to an organization and lead to inertia. Nohria and Gulati (1996) extend this view by hypothesizing and testing for an inverse U-shaped relationship between slack and innovation: In the absence of slack, experimentation cannot be sustained because of the high variance associated with its outcomes; in the presence of too much slack instead, organizations lose any form of discipline in selecting which projects to support and make wasteful investments.

Whereas we incorporate this tension between the positive and negative effects of slack from the literature, we focus on a new, understudied mechanism through which an increase in slack time can shape the allocation of time and effort to innovative projects: the opportunity cost of time. Our economic perspective, grounded in a simple theoretical framework, allows us to derive new predictions about the effect of slack on the rate, quality and type of innovation. Moreover, by endogenously changing the types of ideas being pursued and the amount of effort dedicated to them, our framework based on the opportunity cost of time is able to incorporate some of the familiar predictions from the literature without resorting to additional, strong assumptions.

We also contribute to the literature by focusing on a less studied form of slack, *time*, and by measuring its causal effect on innovation. Most past work has focused on slack financial resources, and has rarely taken advantage of exogenous variation in slack. A key exception is Natividad (2013), who relies on unexpectedly successful projects to estimate the causal effect of an increase in financial resources on firm performance, and finds that slack drives firms to add more projects and imitate—unsuccessfully—what led to the unanticipated positive outcomes in the first place.

Like financial slack, slack time is a resource that affects all types of organizations, teams, and individuals. Although organizations can use financial slack to hire more workers and free up time, time-related slack creates a

distinct set of opportunities from financial slack alone. The opportunity cost of time, in particular, has been shown to dramatically influence the types of research collaborations individuals engage in and breakthrough innovations (Catalini 2017).

Perlow (1999) documents that fragmented time (as opposed to the continuous spells we focus on with college breaks) can have a negative effect on productivity because of the way it disrupts concentration. Time, moreover, is a “network good” (Young and Lim 2014), because its value increases with the ability to coordinate its use with others (Zerubavel 1985), and scheduling conflicts can become a barrier to social relations (Winship 2009). We incorporate these ideas in the analysis of how slack time influences projects that are more likely to benefit from team coordination and diverse skills, generating an additional set of previously untested predictions.

Taken together, the results have novel implications for how organizations design their policies around slack, and surface the need for both stricter screening mechanisms to avoid low-quality contributions, and for overlapping slack between team members to encourage experimentation with complex, high-quality ideas that require coordination between individuals from different functional areas within an organization.

3. Theoretical Framework

This section develops a simple model to explore the impact of slack time on innovation. It captures a key difference between work and break periods: the opportunity cost of time is lower during breaks. In this setting, break weeks should be broadly interpreted as uninterrupted periods of time during which individuals do not need to attend to their regular tasks, but are allowed to experiment with new projects more freely.

We later extend the framework to incorporate a second, important qualitative difference in the nature of time between these two periods: time is less fragmented and coordination among collaborators is easier during breaks (i.e., the “network good” properties of time are more salient during breaks). This gives individuals more flexibility in coordinating schedules and the ability to iterate faster on the development of their projects.³

3.1. Basic Setup

One idea arrives in each period.⁴ The realized value of a project v depends on two factors: the idea’s intrinsic quality q (i.e., its latent potential), and the amount of effort (or, equivalently, *time* in this context) devoted to developing the project, e . We assume that $v = q \cdot e$. Thus, the realized value of a project increases with both the idea’s intrinsic quality and the amount of effort

dedicated to it. The innovator’s payoff from developing an idea at a certain effort level is assumed to be

$$\pi_w = qe - c(e; w), \quad (1)$$

where $c(e; w)$ is the cost of effort, with $w \in \{0 = \text{break}; 1 = \text{work}\}$ indicating the time period. Because the opportunity cost of time is higher during work weeks, $c'(e; 0) < c'(e; 1)$.

It is important to note that we set up the model within the crowdfunding context to better integrate theory and empirics. The basic premises and predictions of the model are, however, more general. To reiterate, the two key assumptions—(1) the opportunity cost of time of working on a new project is lower when an innovator’s routine tasks are less demanding; and (2) given a project’s intrinsic quality, when more time and effort is devoted to its advancement, the value of the project increases—are, by no means, specific to the crowdfunding setting. These assumptions apply to a range of settings, including employees allocating time between routine and nonroutine projects within a firm.

To obtain analytical results, we assume that the idea quality q follows an exponential distribution and that the cost function is convex in effort: $c(e; w) = c_w \frac{e^2}{2}$, with $c_0 < c_1$.⁵ The payoff in Equation (1) can be rewritten as

$$\pi_w = qe - c_w \frac{e^2}{2}. \quad (2)$$

The first-order condition yields the optimal effort level as $e_w^* = q/c_w$. Thus, given any quality level, less effort is spent when time is more precious (i.e., when there is less slack time); when given the same opportunity cost of time, more effort is spent when the idea is better (i.e., individuals endogenously allocate effort based on the latent potential of an idea). Inserting e_w^* back into Equation (2), we obtain the innovator’s payoff at the optimal level as $\pi_w^*(q) = \frac{q^2}{2c_w}$.

A campaign page on a crowdfunding platform typically includes a description of the project, the amount requested, information on deliverables and implementation plan, and background information on the project creators. Creating such a page requires substantial effort, which naturally screens out low-quality projects (for which applying effort to create a page is not worthwhile). We operationalize this in the model by introducing $\bar{e}$, which is the minimum amount of effort required to have a project accepted by the platform. As mentioned before, a key side effect of slack is its negative effect on the quality of projects being pursued. Organizations that want to provide slack to encourage experimentation, but that also want to prevent the creation of too many, low-quality projects, can combine it with a selection mechanism targeted at curtailing such projects. In the model, this

would be represented by an increase in $\bar{e}$. In Section 5.4, we explore what happens to the types of projects posted when—because of a sudden policy change on Kickstarter—this threshold is exogenously increased in two of its categories and innovators face an organizational change targeted at reducing low-quality contributions.

Denote the innovator's payoff at the minimum required effort level as $\tilde{\pi}_w(q) = q\bar{e} - c_w \frac{\bar{e}^2}{2}$. Taking into account the minimum effort requirement, the innovator's payoff can be written as

$$\tilde{\pi}_w(q) = \begin{cases} \mathbb{I}_{\{q \geq c_w \bar{e}\}} \frac{q^2}{2c_w} + \mathbb{I}_{\{q < c_w \bar{e}\}} (q\bar{e} - c_w \frac{\bar{e}^2}{2}) & \text{if the project is developed} \\ 0 & \text{if the project is dropped,} \end{cases} \quad (3)$$

where $\mathbb{I}_{\{\cdot\}}$ is an indicator function. An innovator who develops a project obtains $\pi_w^*(q) = \frac{q^2}{2c_w}$ when the quality of the idea is sufficiently high (when $q \geq c_w \bar{e}$). In this quality range, the optimal amount of effort is above the minimum requirement. For ideas of relatively low quality (when $q < c_w \bar{e}$), the innovator's payoff is $\tilde{\pi}_w(q) = q\bar{e} - c_w \frac{\bar{e}^2}{2}$, because the optimal effort is below the required level. In this range, the innovator overdevelops the project (relative to the desired amount of effort given the quality of the idea) to meet the minimum requirement and obtains a payoff that is below the desired level. Despite this, the innovator still develops the project if $\tilde{\pi}_w(q) > 0$, which is the normalized outside option.

Figure 1(a) illustrates the innovator's payoffs separately for break and work periods using a numerical example. Given any idea quality q , the innovator's payoff for a break is higher than a work period. This is because the opportunity cost of time is lower during breaks and, at the same time, the project's value increases as more time is spent on it. It is straightforward to show that the innovator develops an idea only if its quality is above a certain threshold and that this threshold is less stringent during breaks.⁶ Thus, we have Prediction 1 (see Online Appendix A1 for the proof and other results):

Prediction 1 (Differences in Quantity). More ideas are developed during break periods than work periods.

The value of a completed project is

$$\tilde{v}_w(q) = \mathbb{I}_{\{q \geq c_w \bar{e}\}} \frac{q^2}{c_w} + \mathbb{I}_{\{\frac{c_w \bar{e}}{2} < q < c_w \bar{e}\}} q\bar{e}. \quad (4)$$

Notice that ideas with quality $q < \frac{c_w \bar{e}}{2}$ are dropped. Figure 1(b) illustrates the value of developed projects as a function of idea quality. It highlights two consequences of a lower opportunity cost of time on the overall value

of posted projects. First, because time is less costly, the innovator is less selective when screening out ideas. Thus, the value of some of the projects developed during breaks is lower than any project developed during a work period (i.e., a “selection effect”). Second, also because time is less costly, the innovator can work more on any given idea and improve it. This “effort effect” increases a project's value v , given the same intrinsic starting quality q .

The comparison of the average value of projects between work and break periods is ambiguous because the two effects discussed above push it in opposite directions. We therefore compare the distributions directly. Figure 1(c) plots the conditional densities of developed projects by their value v using the same numerical example in Figure 1, with q following an exponential distribution. Compared with work periods, there are disproportionately more projects at the low end of the distribution during breaks because the innovator is less selective about screening out bad projects. At the same time, there are also more projects at the high end of the distribution, because the idea quality required to achieve a certain project value is lower during breaks as a result of the effort effect.

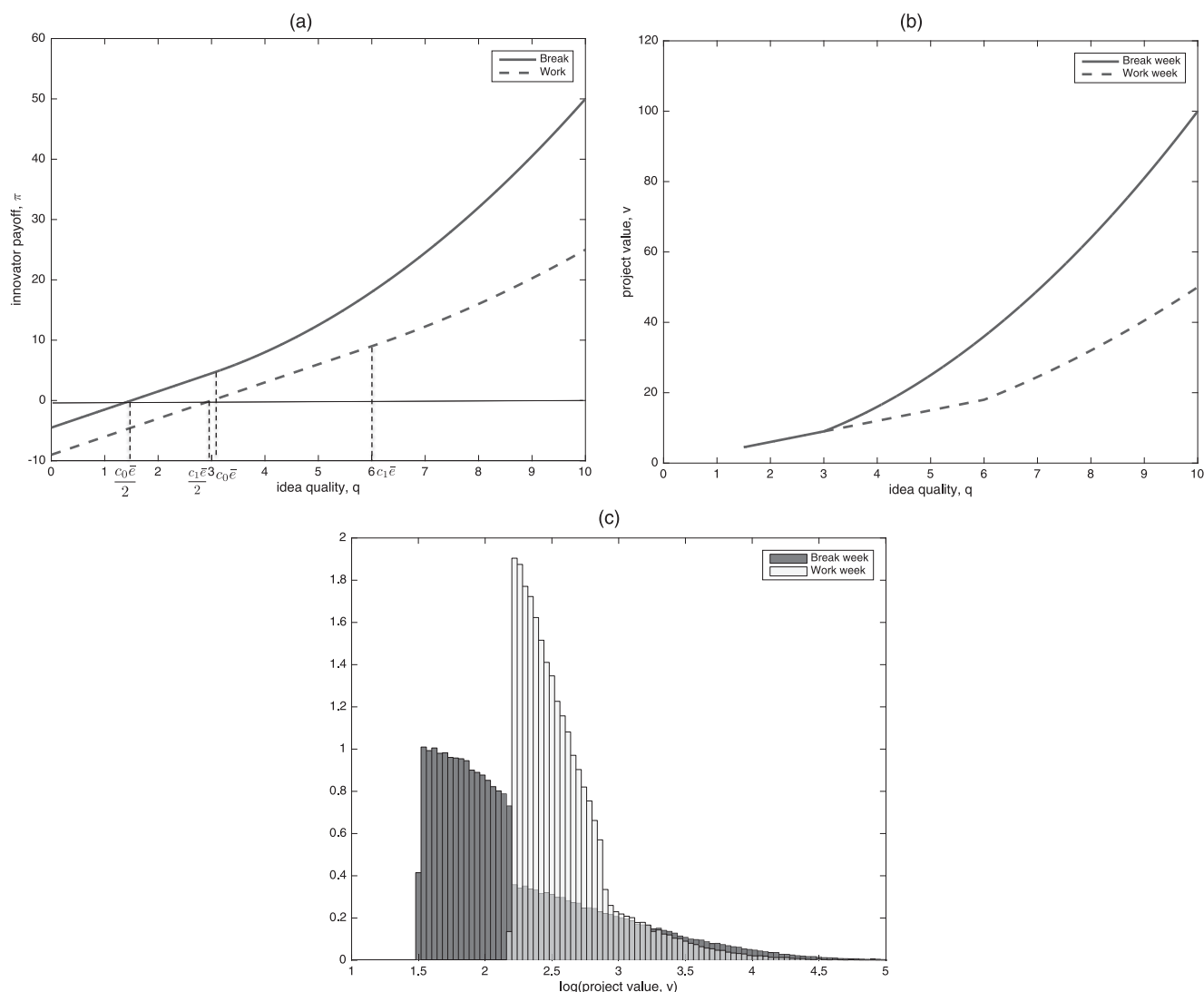
Prediction 2 (Differences in the Distribution of Project Value, Conditional on Development). Relative to work periods, projects developed during breaks are both more likely to be at the low end ($v < \frac{c_1 \bar{e}^2}{2}$) and at the high end of the distribution ($v \geq c_1 \bar{e}^2$).

The above result hinges on the assumption that more effort makes projects better. As illustrated in Figure 1(b), the innovator can achieve the same value v with a lower-quality idea during a break because more time can be devoted to improving a project. Prediction 3 builds on this observation.

Prediction 3 (Differences in Effort). For projects with the same value v , the amount of effort spent on projects developed during breaks is greater than (or equal) to the amount of effort spent on projects developed during work periods. Furthermore, the difference in effort is greater for projects of higher value v .

We now explore the impact of an increase in the minimum effort requirement $\bar{e}$. Overall, a more stringent posting requirement should increase the quality thresholds for both break and work periods and, as a result, fewer projects should be developed. The relative size of the reductions, however, is ambiguous. On the one hand, the increase in the threshold per se is greater for work periods (i.e., $\frac{\partial \bar{q}_1}{\partial \bar{e}} = \frac{c_1}{2} > \frac{\partial \bar{q}_0}{\partial \bar{e}} = \frac{c_0}{2}$), which is intuitive because increasing the effort requirement is more taxing when time is more precious. On the other hand, because the distribution of idea quality q is likely to be skewed to the left, the number of

Figure 1. Numerical Illustration of the Model: Innovator's Payoff, Value of Developed Projects, and Density Distribution of Project Value, Conditional on Development



Notes. (a) Plot of the innovator's payoff from developing a project as a function of the idea's intrinsic quality, q . (b) Plot of the value of developed projects as a function of the idea's intrinsic quality, q . (c) Plot of the probability density distributions of v conditional on development. The parameter values of the numerical example are $c_0 = 1$; $c_1 = 2$; and $\bar{e} = 3$. In addition, for panel (c), idea quality q is assumed to follow an exponential distribution with mean 1.5.

projects dropped may be greater during breaks if these periods encourage more low-quality projects to begin with.

Prediction 4 (Effect of Increasing the Minimum Effort Requirement $\bar{e}$ on Relative Quantities). When the distribution of idea quality q is not too skewed to the left (when the mean of the exponential distribution is greater than $\frac{c_1 \bar{e}}{2}$), the reduction in quantity due to an increase in the minimum effort requirement is smaller for breaks than work periods.

For both break and work periods, the expected value of projects developed should be higher after an increase in the posting requirements. The relative size of

the increases is ambiguous, and depends on the parameter values and the distribution of q . However, because such a policy shock does not affect projects of high quality (they are always above the selection threshold), the share of top-valued projects developed during breaks (relative to the total number of projects developed during both periods) should increase. That is:

Prediction 5 (Effect of Increasing the Minimum Effort Requirement $\bar{e}$ on Relative Project Value). The share of top-valued projects developed during breaks (relative to the total number of projects developed during both periods) increases after an increase in the minimum effort requirement.

4. Data and Empirical Strategy

The empirical setting is Kickstarter, the world-leading reward-based crowdfunding platform. We collect data for the 165,410 U.S.-based projects that attempted to raise money on the platform between April 2009 and April 2015. Project-level information that is publicly available includes the time each project was posted, total funds raised, the project description, and the background of the entrepreneur(s). We do not have comprehensive data on the timing of individual contributions to a project or the location of the funders.⁷

The platform attracts innovative projects in the early phases of their development. Depending on the sector, entrepreneurs may have working prototypes of their product or a concrete plan for the final deliverable (e.g., a concert). The crowd is typically asked to fund the “R&D” needed to implement the plan and turn such prototypes into an early adopter version that can be ultimately mass produced. While the invention phase may be concluded by the time some of the projects are posted, in most cases there is still substantial market and technical uncertainty that needs to be resolved before commercialization.

As crowdfunding platforms have expanded, this market for online capital has become very competitive. Launching a successful campaign requires substantial marketing, PR and social media effort targeted at building a community of early supporters. Moreover, a campaign page needs to offer high-quality video, text, and graphics to attract the crowd’s limited attention in a context where thousands of projects are posted every day. Campaigns also require constant attention and care after they are launched, and project creators need to meaningfully engage with the crowd through Q&A and updates to maintain fundraising momentum.⁸

Kickstarter requires projects to state a funding goal in advance. If a project fails to achieve its funding goal, then the capital is returned to funders and the entrepreneur does not receive any money. We label projects that achieve their funding goal as “successful” and the ones that do not as “failed.” Projects in the data collectively raised \$1.4 billion, including both successful projects (44% of projects and 89% of raised capital) and failed projects (56% of projects and 11% of raised capital, which is eventually returned).

We use funds raised as a proxy for a project’s commercial potential and revealed market demand. Similar to offline capital raised by startup founders, capital raised on the platform is among the best available, systematic measures of the commercial potential of an entrepreneurial project. As previously documented (Agrawal et al. 2013), the distribution of capital is highly skewed: the top 1% (10%) of projects accounts for \$590 million (\$1 billion), or 42% (76%) of the capital.

Kickstarter identifies a city for each project based on the location reported by the entrepreneurs. This provides a smaller geographic measure than a core-based statistical area (CBSA) and a larger one than a Census Place. We use city as the location measure in the analysis because it does not involve further aggregation or disaggregation of the core dependent variables. The sample projects span 10,091 U.S. cities, taken from Kickstarter’s list on its website.

Kickstarter is widely used in many college towns. For example, Boulder, Colorado; Provo, Utah; and Ann Arbor, Michigan, are among the top 10 places for technology projects per capita. In light of the prominence of locations with colleges on Kickstarter, the empirical analysis exploits the week-by-week variation in the extent of slack time in these places. We manually collect data on school breaks between 2009 and 2015 for the top 200 U.S. colleges as defined by *U.S. News & World Report*.⁹ This information is publicly available through posted academic calendars. We consider a location to have a school break in a given week if there is a top 200 college within 5 miles of the city center and the college has a break that week. In addition to scheduled breaks, we also manually collect data on snow days from school websites, Twitter, and online news reports.

Table 1 presents descriptive statistics at the city-week level for the sample. Approximately 3.3% of the observations are city-weeks, where at least one of the top 200 colleges is on break, and Table 2 compares key outcome variables between break weeks and work weeks, providing model-free evidence for some of the basic predictions of the model.

During the study period, the average city-week had 0.052 projects launched, with slightly more than half (0.029) failing to reach their goal and the remainder (0.023) successfully reaching it. In most city-weeks, no projects are launched. Relative to work weeks, the number of projects per week is significantly higher for breaks (0.39 versus 0.04).¹⁰

We use three different proxies for effort in the analysis: the length of the text (in words) used to describe a project, the number of frequently asked questions (FAQs) the entrepreneur lists on the page, and the number of project updates posted. Relative to work weeks, the descriptive statistics show that projects posted during breaks have longer descriptions, more FAQs, and more updates. We also examine the impact of breaks on team projects and how that varies with project complexity. We capture team projects by identifying the number of team members listed on the projects’ biography pages. Overall, 3% of projects are posted by teams. Relative to work weeks, a significantly greater percentage of projects posted during breaks use teams (12.8% versus 2.7%). Using the biographies, we also identify the skills mentioned by creators in their profiles (e.g., programming, photography).

Table 1. Summary Statistics

	N	Mean	Standard deviation	Minimum	Maximum
Projects	3,178,665	0.052	0.761	0	114
Total successful projects	3,178,665	0.023	0.398	0	45
Total failed projects	3,178,665	0.029	0.425	0	79
Funding	3,178,665	444.686	23,633.61	0	21.8M
Total successful funding	3,178,665	393.86	23,149.05	0	21.8M
Total failed funding	3,178,665	50.821	1,784.375	0	623,041
All breaks	3,178,665	0.033	0.178	0	1
Snow closing	3,178,665	0.001	0.034	0	1

We use the resultant measures to build two proxies for project complexity: the number of unique skills listed, and the number of unique skills divided by the size of the team (to avoid a mechanical relationship between team size and the total number of unique skills). Among projects posted, the mean number of skills is 1.5, and the mean number of skills per team member is 1.2. These values are higher for projects posted during breaks.

Overall, the raw data are consistent with the basic predictions of our framework: break weeks are characterized by significantly more projects, and more effort devoted to the posted projects. Furthermore, we observe an increase in project complexity and the use of teams. However, because these differences might be driven by a number of confounding factors such as time trends, seasonality, and differences in the baseline level of crowdfunding activity across cities, we control for these differences using the empirical strategy described below.

4.1. Empirical Strategy

The econometric framework we use is straightforward: we exploit variation across cities in the timing of breaks at local colleges and universities to estimate how an increase in slack time influences the number and type of projects posted. The unit of analysis is a city-week. City fixed effects are included to control for underlying differences across cities that are constant over time, and week fixed effects are added to control for changes in the Kickstarter environment over time. We focus on a linear model with fixed effects to document the underlying relationships in a direct and easily interpretable manner:

$$Y_{ct} = \gamma AllBreaks_{ct} + \mu_c + \psi_t + \epsilon_{ct},$$

where Y_{ct} is the outcome variable such as the number of projects posted on the platform in city c during week t ,¹¹ $AllBreak_{ct}$ is a dummy that equals one if there is a top 200 college in the focal city on break in the focal week, μ_c and ψ_t are city and week fixed effects, and ϵ_{ct} is an idiosyncratic error term. There are few city-level measures that change at the week level. Unsurprisingly, given city and week fixed effects, results do not change when including controls such as weekly temperature and annual CBSA-level demographics. Thus, we focus on the more parsimonious specification and do not include additional covariates. Because the fixed effects completely capture cities in which we never see any crowdfunding activity, we remove these cities from the analysis without any empirical consequence. Robust standard errors are clustered at the city level for all regressions.

5. Results

We first present regression results on the quantity of projects posted. Consistent with the raw data, a substantially greater number of projects are posted during break weeks. We follow this main result with evidence supporting a causal interpretation. Second, we report results on the impact of breaks on the distribution of project value. Third, we examine differences in project complexity and the likelihood of teams during break weeks versus work weeks. The results are informative about the role that uninterrupted time plays in reducing coordination costs. Finally, we exploit a Kickstarter policy change that increased the posting requirement in some but not all project categories to test the effect of a stricter selection threshold on curtailing the negative effects of slack time on innovation quality.

Table 2. Comparing Break and Work Periods

	Difference	Standard error	p-value	Break		Work	
				N	Mean	N	Mean
Projects	0.356	0.002	0	104,440	0.396	3,074,225	0.040
Funding	3700.27	74.33	0	104,440	4023.38	3,074,225	323.11
log Funding	0.613	0.004	0	104,440	0.755	3,074,225	0.141

Table 3. Impact of Breaks on the Quantity of Projects

Variables	(1) Projects	(2) Funding	(3) log Funding
<i>All breaks</i>	0.0238*** (0.0083)	20.9730 (259.5038)	0.0155*** (0.0039)
Observations	3,178,665	3,178,665	3,178,665
R-squared	0.164	0.003	0.787
Number of cities	10,091	10,091	10,091

Notes. The dependent variables are, respectively, the number of projects in a city-week, the total amount of funding, and log(Funding +1). City and week fixed effects are included in all regressions. Robust standard errors are clustered at the city level.

*** $p < 0.01$.

5.1. Quantity of Ideas Developed (Prediction 1)

Column 1 of Table 3 shows that, controlling for week and city fixed effects, the number of crowdfunding campaigns launched increases during school breaks by 0.024 (significant at the 1% level). The magnitude of the increase is substantial relative to the average number of campaigns per city-week of 0.052 (first row in Table 3), implying an increase of 45%.

In terms of the total amount of funds raised, we use funding (not logged) as the dependent variable in column 2 of Table 3. The estimated coefficient on school breaks is also positive but not significantly different from zero. This is likely because the distribution of funding is highly skewed. Thus, we use log(Funding+1) as the dependent variable in column 3. The result shows a positive and significant correlation between total funding and college breaks, with an increase of about 1.5%.¹² In Table 4, we divide our sample by locations with an above versus below the median share of college students based on the American Community Survey: consistent with our interpretation of the main result, the effect of breaks is entirely driven by locations with a high student presence (column 2).¹³

5.1.1. Evidence for a Causal Interpretation. The mechanism behind Prediction 1 suggests that the positive correlation between the quantity of projects and breaks is causal: breaks enable more projects to be developed because the opportunity cost of time is lower. By

including city and week fixed effects, the basic empirical strategy helps isolate a potentially spurious correlation due to general time trends, seasonality, or time-constant differences in innovative activity across cities. In the rest of this subsection, we provide additional evidence in support of a causal interpretation of this relationship.

First, we exploit variation across types of universities and Kickstarter categories to examine whether the spike in activity is consistent with the type of human capital involved. We do this because, although we obtain variation in breaks using university-level data, we measure activity at the city level. Thus, demonstrating that the city-level effect (e.g., more technical projects posted on Kickstarter) is consistent with local university-level human capital (e.g., break week for an engineering school as opposed to an art school) provides further evidence that is consistent with our interpretation. In column 1 of Table 5, we use only projects in art, and in column 2 we focus on projects in technology.¹⁴ Breaks at top art, design, film, and theater schools are positively correlated with art projects but not technology projects. Conversely, breaks at top engineering schools are positively correlated with technology but not art projects, consistent with the expectation that technical orientation plays a key role in these types of projects. Relatedly, in column 3 of Table 5, we run the main specification only for projects where we are able to identify the presence of a student on the team using the biographies posted on

Table 4. Robustness to Sample Definition by County-Level College Enrollment

Variables	(1) Below median college students	(2) Above median college students
<i>All breaks</i>	-0.0084 (0.0069)	0.0257*** (0.0090)
Observations	1,589,175	1,589,490
R-squared	0.621	0.142
Number of cities	5,045	5,046

Notes. The dependent variable is the number of projects. Columns 1 and 2 separate the sample by whether the associated counties have above or below the median number of college students, according to the American Community Survey (ACS). City and week fixed effects are included in all regressions. Robust standard errors are clustered at the city level.

*** $p < 0.01$.

Table 5. Impact of Breaks on the Quantity of Projects: Robustness Checks

Variables	(1) Artistic projects	(2) Technology projects	(3) Student projects	(4) All projects	(5) All projects, year data	(6) Funding days 8–14	(7) log Funding days 8–14	(8) All projects	(9) Clearly shelved	(10) Excluding shelved
<i>All breaks</i>	0.0020 (0.0013)	0.0003 (0.0004)	0.0034** (0.0017)	0.0495*** (0.0121)		96.3529 (88.8682)	0.0256 (0.0162)	0.0447*** (0.0129)	0.0012** (0.0005)	0.0435*** (0.0126)
<i>Break at top engineering school</i>	–0.0007 (0.0032)	0.0024** (0.0011)								
<i>Break at top art, design, film, or theater school</i>	0.0053* (0.0028)	0.0003 (0.0009)								
<i>Snow closing</i>				0.0403** (0.0178)	1.2407*** (0.4758)					
Observations	1,604,469	1,604,469	3,178,665	2,966,754	50,455	1,321,921	1,321,921	2,754,843	2,754,843	2,754,843
R-squared	0.001	0.000	0.003	0.008	0.013	0.000	0.002	0.164	0.011	0.164
Number of cities	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091

Notes. The dependent variable in column 1 is the number of art-intensive projects, and in column 2 it is the number of technology-intensive projects (available May 2012 to April 2015). In column 3, the dependent variable only includes projects in which the creators explicitly mention their student affiliation in their biography. Columns 4 and 5 use data on snow closings (available until December 2014). The unit of analysis for column 5 is the city-year level. Columns 6 and 7 use data on weekly investments (available from October 2012 to April 2015). City and week fixed effects are included in all regressions (with the exception of column 5, which uses year fixed effects because of the different unit of analysis). Columns 8 to 10 use data on shelved projects (data are available from the beginning of the sample to July 2014); in particular, column 8 includes all projects for this subsample, column 9 only captures projects that we identified as clearly shelved by their creators based on the project page, and column 10 removes from all projects those that were clearly shelved. Robust standard errors are clustered at the city level.

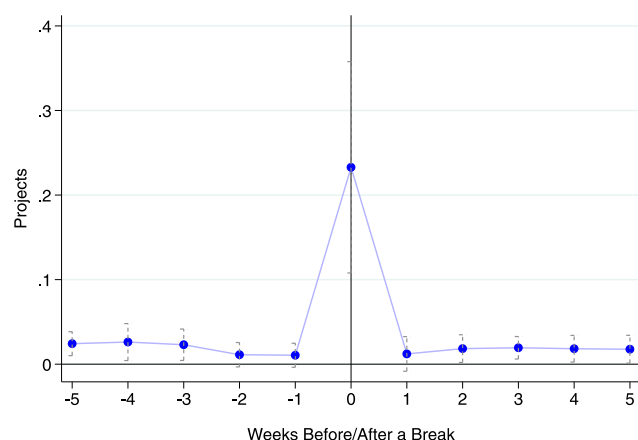
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Kickstarter. The estimated effect is 0.0034. Relative to the mean of the dependent variable, 0.0066, the effect of breaks in this sample is a 51% increase in projects, which is higher than the 45% increase we observe in the full sample.

Second, we examine the impact of an unexpected increase in the amount of slack time using college closings due to heavy snow. Column 4 of Table 5 shows that snow breaks are also associated with a significant and positive increase in the quantity of projects. In addition, column 5 uses the city-year as the unit of observation and regresses the number of projects on the total number of snow days in that city-year, controlling for city and year fixed effects. Given that the number of days that a college cancels classes due to snow varies exogenously from year to year and city to city, the positive and significant coefficient is consistent with such random increases in slack time having a positive, causal impact on the number of projects produced.

Third, if breaks provide college students with more time to browse Kickstarter and fund projects, then the result may be driven by an increase in the supply of local capital. To assess this alternative explanation, we examine the timing of funding associated with projects posted in the week preceding a break. In particular, we measure whether funding for those projects increased during the break. For consistency, we specifically look at 8–14 days after posting. If the effect we measure is due to increased funding during a break, then we would expect to observe an increase in funding during break weeks for projects posted *just prior* to the break. However, results reported in columns 6 and 7 of Table 5 indicate that funding associated with projects started during a work week does not rise during break weeks even though fundraising efforts continue during those weeks.

It is important to highlight that the breaks we explore in the main analysis are scheduled and expected, and therefore people might shelve ideas and wait until they have more time to develop them.¹⁵ Shelving per se does not invalidate the causal impact of breaks. What is important is that the completion of some critical tasks benefit from the availability of more time. The slack time provided by the breaks offers uninterrupted periods where students can focus, push their projects further and team coordination is easier. In the absence of slack, these ideas are likely to stay undeveloped for a longer period of time or not be developed at all (in the same way employees at a firm may have ideas about improving a product or service, but may not have the time and resources to develop them until they are offered the opportunity to do so in a structured way).¹⁶ Although it is empirically difficult to capture shelving, for a subset of projects, we were able to collect information on when the creator started working on the idea (columns 8–10 of Table 5).

Figure 2. (Color online) Number of Projects per Week Is Higher During Breaks

Notes. Estimated coefficient for weeks before and after the school breaks. The dependent variable is the number of projects created in the focal city-week. Regression includes city and week fixed effects. Error bars represent 95% confidence intervals based on robust standard errors clustered at the city level.

Excluding these projects that have been clearly shelved (column 10) does not affect our results.

We also do not observe strong evidence of shelving in the data. Figure 2 plots the regression results that include dummies for the weeks before and after a college break period in the main specification, and the baseline is any week more than five weeks away from a college break. The figure shows no *decrease* in activity immediately before or after a break. This lack of a pretrend is inconsistent with individuals shifting the development of their ideas in anticipation of a break.

5.2. Project Value Distribution and Effort (Predictions 2 and 3)

In the previous section, we show that when college students are on break in a city, there are substantially more projects posted and more funds raised on Kickstarter. The increase in quantity may have different implications depending on the quality of these additional projects. Prediction 2 suggests that relative to work weeks, during breaks we should observe disproportionately more projects at both the low end and the high end of the value distribution. This prediction arises from the lower opportunity cost of time during breaks inducing (1) more marginal projects to be pursued because time is less precious (a selection effect) and (2) more effort to be allocated to the development of an idea, which, in turn, increases project value (an effort effect).

To examine the impact of breaks on the distribution of project value, we divide projects into 15 bins based on the amount of funds raised (the bins are defined by year to account for the growth of the platform). Table 6 reports the results from a regression in which

the dependent variable is the number of projects in a specific bin, the unit of analysis is a city-week-bin, and fixed effects for weeks and cities are included as in the previous tables. The results are consistent with Prediction 2: relative to work weeks, breaks are characterized by significantly more projects of the lowest value (bin 1), fewer projects in the middle of the distribution (bins 2–6), and more projects on the right tail of the distribution (bins 7–15). Furthermore, the effects become increasingly larger and more significant as we move away from the middle of the distribution.¹⁷

Recall that the model assumes that given a project's latent quality, more effort makes it better, which

Table 6. Impact of Breaks on Project Value Distribution

Variables	Projects
<i>All breaks × Bin 1 (lowest value)</i>	0.0091*** (0.0019)
<i>All breaks × Bin 2</i>	−0.0115*** (0.0024)
<i>All breaks × Bin 3</i>	−0.0018 (0.0012)
<i>All breaks × Bin 4</i>	−0.0015 (0.0011)
<i>All breaks × Bin 5</i>	−0.0013 (0.0012)
<i>All breaks × Bin 6</i>	−0.0012 (0.0008)
<i>All breaks × Bin 7</i>	0.0003 (0.0008)
<i>All breaks × Bin 8</i>	0.0007 (0.0005)
<i>All breaks × Bin 9</i>	0.0025*** (0.0008)
<i>All breaks × Bin 10</i>	0.0024** (0.0010)
<i>All breaks × Bin 11</i>	0.0028** (0.0014)
<i>All breaks × Bin 12</i>	0.0050** (0.0020)
<i>All breaks × Bin 13</i>	0.0053** (0.0024)
<i>All breaks × Bin 14</i>	0.0061** (0.0029)
<i>All breaks × Bin 15 (highest value)</i>	0.0063* (0.0034)
Observations	47,679,975
Number of cities	10,091
R-squared	0.031

Notes. The dependent variable is the number of projects in a specific bin of project value, and the unit of analysis is a city-week bin. We divide projects into 15 bins based on the amount of funds they raise, from the lowest (bin 1) to the highest (bin 15). Bins are defined by year to account for the growth of the platform. City and week fixed effects are included the regression. Robust standard errors are clustered at the city level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

explains why we observe a positive effect of breaks on the right tail of the project value distribution. It is therefore important to see whether the data are consistent with this mechanism. In particular, Prediction 3 shows that we should observe more effort during breaks and that the difference in effort should be larger for projects of higher value. This prediction is confirmed by the results reported in Table 7. First, columns 1–3 show that the average values for the three different proxies for effort (length of project description, number of FAQs, and number of updates) are all significantly higher for projects posted during breaks.¹⁸ Second, when we separate projects into different bins of the value distribution, results show that for all measures of effort, the difference between break and work weeks increases as we move from the lowest bins (columns 4, 7, and 10) to the highest ones (columns 6, 9, and 12).

In sum, the results of this section are consistent with the model's prediction that we should observe disproportionately more projects on both tails of the value distribution. The right tail is particularly interesting because these projects are more likely to have a disproportionate impact. The results on effort seem to corroborate the mechanism we hypothesized for the creation of these high-impact projects; that is, entrepreneurs are able to devote more effort to executing on their ideas when the opportunity cost of time is lower. It is useful to highlight that our result on the distribution of project value can also be explained by a change in the risk profile of the projects being pursued. If the innovator is risk averse and the project value is ex ante uncertain, lowering costs in general (and the opportunity cost of time in particular) may lead to the development of a greater number of risky projects and, thus, a greater likelihood of both low-value and high-value projects.¹⁹

This behavior has been observed for scientists following a reduction in distance-related costs and opportunity cost of time (Catalini 2017) and for entrepreneurs (Nanda and Rhodes-Kropf 2016). Recall that there is no uncertainty in our model and that the lower opportunity cost of time increases projects on both tails of the outcome distribution because of a selection effect (some low value projects are now worth developing) and an effort effect (more time and effort can be dedicated to high value projects). Because it is difficult to imagine an innovative project without any ex-ante uncertainty or an innovative project that would not benefit from effort, both mechanisms (the one proposed in our model, and the one based on uncertainty and risk-averse entrepreneurs) are likely to coexist.

The uncertainty mechanism does not explicitly model effort; hence, it has no predictions about this variable. Effort, however, is an important building block in our

framework, and Prediction 3 has clear implications for the impact of breaks on the amount of effort devoted to a project and how they relate to project value. The results presented in Table 7 are consistent with this prediction, providing further support for our theoretical approach. That said, we want to emphasize that we cannot rule out the uncertainty mechanism discussed above and that it may also play a role in driving the distribution of project value.

5.3. Teams and Project Complexity

Projects may be carried out by teams for at least two intuitive reasons: (1) with multiple people sharing the workload, a team can achieve more than a single person, and (2) complex projects may require people with complementary skills and perspectives. The downside of a team, however, is that it requires coordination, and this may become especially daunting as project complexity and the interdependence between its different components increases. In Online Appendix A2, we extend the baseline model to examine the use of teams. In addition to differences in the opportunity cost of time, the extension captures a second distinction between break and work periods: teamwork is more effective during breaks because coordination is easier.²⁰ The extension yields the following predictions. First, the comparative advantage of breaks from a teamwork perspective is most salient for complex projects, and less relevant for simple projects. We should therefore observe a greater share of complex projects during breaks. Second, because forming a team can also help share the workload, and this may be more valuable when time is scarce (i.e., during work weeks), the effect of slack time on the number of team members is ambiguous. However, if we contrast complex projects to simple ones, the predictions are clear cut, and we should see more teams during breaks for complex projects relative to simple ones.

The empirical results are consistent with these predictions. As mentioned before, we use two proxies for project complexity: the number of unique skills on a project (as captured from the biographies of the entrepreneurs), and the number of unique skills divided by team size. Columns 1 and 2 of Table 8 show that for both measures, projects posted during breaks appear to be significantly more complex than projects posted during work weeks. Consistent with the raw data, the regression results also show that on average projects posted during breaks are significantly more likely to be carried out by teams than projects posted during work weeks (column 3 of Table 8). However, results are different when we separate the sample into relatively complex projects versus simpler ones.²¹ For relatively complex projects (columns 4 and 6), the likelihood of teams is significantly higher during breaks. In contrast, for simpler projects (columns 5 and 7), there is

Table 7. Differences Between Breaks and Work Periods in (Endogenous) Effort Provision

Variables	(1) Mean description length	(2) Mean FAQs	(3) Mean updates	(4) 0–33 Mean description length	(5) 33–66 Mean description length	(6) 66–100 Mean description length	(7) 0–33 Mean FAQs	(8) 33–66 Mean FAQs	(9) 66–100 Mean FAQs	(10) 0–33 Mean updates	(11) 33–66 Mean updates	(12) 66–100 Mean updates
All breaks	1.6298*** (0.5042)	0.0093*** (0.0019)	0.0185** (0.0072)	0.8673** (0.4007)	1.2517*** (0.4561)	1.9980*** (0.5826)	0.0054*** (0.0010)	0.0047*** (0.0012)	0.0071*** (0.0022)	0.0075*** (0.0028)	0.0144*** (0.0048)	0.0263*** (0.0089)
Observations	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665
R-squared	0.466	0.079	0.203	0.158	0.166	0.152	0.016	0.027	0.038	0.042	0.081	0.102
Number of cities	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091

Notes. The dependent variables are proxies for effort on the platform. In columns 1 and 4–6, we use the mean length of the project description; in columns 2 and 7–9, the mean number of FAQs; in columns 3 and 10–12 the mean number of project updates to the crowd. In columns 4–12, we progressively divide the projects into three segments based on the bins defined in Table 6. For example, the “0–33” category includes the bottom five bins containing projects that raised the lowest amount of funds and “66–100” the highest. City and week fixed effects are included in all regressions. Robust standard errors are clustered at the city level.

** $p < 0.05$; *** $p < 0.01$.

no significant difference between break and work periods in the likelihood of using a team.²²

5.4. Effect of Increasing the Minimum Effort Requirement (Predictions 4 and 5)

In May 2012, Kickstarter implemented a policy that disproportionately increased the requirement for posting projects in two of its categories. In the context of the model, the new policy increases the minimum effort required to develop a project. Whereas it is ambiguous whether the relative share of projects posted during breaks should increase after the policy change (Prediction 4), the model predicts that we should observe an increase in the share of top-valued projects (Prediction 5). In other words, the shock should limit the negative effect of slack on innovation by reducing the relative number of low-quality contributions. In response to a series of high-profile design and technology projects that raised a significant amount of capital and then failed to deliver the promised products in the anticipated amount of time (some delivered very late and others failed to deliver at all), Kickstarter increased the requirements for posting projects in those two categories. One of the primary criticisms was that in most of these cases the entrepreneurs raised capital and promised a product without any experience or preparation for production or distribution. Therefore, in May 2012 Kickstarter revised its rules to address accountability concerns, explaining in a note that it now required project creators to “provide information about their background and experience, a manufacturing plan (for hardware projects), and a functional prototype. [Kickstarter] made this change to ensure that creators have done their research before launching and backers have sufficient information when deciding whether to back these projects.”²³ The policy was further reinforced in September 2012, when Kickstarter reiterated the need for a prototype and made it clear that product simulations and renderings were not enough.²⁴

The regression results in Table 9 contrast the relative changes in a number of key outcome variables for break weeks versus work weeks before versus after the policy shock for projects in the design and technology categories relative to the other 11 categories. First, for the relative changes in the quantity of projects, we use a regression in which the dependent variable is the ratio between the number of projects in design and technology and the number of projects in all other categories (column 2 of Table 9). The coefficient of the interaction term between breaks and the period following the policy change is positive and significant. This suggests that when comparing across categories, breaks are associated with an increase in the relative number of projects in the categories affected by the

Table 8. Differences Between Breaks and Work Periods in Project Complexity and the Share of Teams

Variables	(1) Mean skills	(2) Mean skills PP	(3) Mean team size	(4) Share team in complex (skills)	(5) Share team in simple (skills)	(6) Share team in complex (skills PP)	(7) Share team in simple (skills PP)
<i>All breaks</i>	0.0066*** (0.0018)	0.0046*** (0.0016)	0.0024* (0.0014)	0.0009** (0.0004)	0.0004 (0.0004)	0.0009** (0.0004)	0.0007 (0.0005)
Observations	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665
R-squared	0.350	0.322	0.458	0.049	0.065	0.107	0.164
Number of cities	10,091	10,091	10,091	10,091	10,091	10,091	10,091

Notes. For columns 1 and 2, the dependent variables are the mean level of measures of project complexity for all projects in a given city-week. The two measures we use are the unique number of skills (“skills”) and the unique number of skills per person on the team (“Skills PP”). For columns 3–7, the dependent variable is the share of team projects among all projects for a given city-week. We define complex projects as those that are above the median in terms of the two complexity measures (and simple projects as those below the median). City and week fixed effects are included in all regressions. Robust standard errors are clustered at the city level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

shock. Column 4 of Table 9 shows a similar result for the relative amount of funding.²⁵ Second, for project value, column 6 of Table 9 reports results from a regression in which the dependent variable is the ratio between the share of projects with large target amounts (over \$30,000) in design and technology and the share of such projects in other categories. Consistent with Prediction 5, the coefficient of the interaction term shows that after the policy change, relative to other categories, the share of large-goal projects significantly increased during break weeks in the affected categories. Finally, column 8 of Table 9 shows that after the shock, the relative likelihood of using teams during breaks increases disproportionately for design and technology projects relative to other categories. Intuitively, this result is consistent with breaks facilitating team coordination. A more stringent posting requirement makes teams relatively more desirable because multiple people can share the workload and tackle the increased complexity.

6. Conclusion

We explore how slack time influences the quantity, quality, and type of innovation. We focus on a novel mechanism through which slack time can shape inventive outcomes: the opportunity cost of time. Lower opportunity cost time may induce (1) lower quality ideas to be developed (a selection effect); (2) more effort to be applied (an effort effect); and (3) an increase in the use of teams because scheduling is less constrained (a coordination effect).

The approach leads to a number of novel results. First, during breaks, more projects are posted on Kickstarter in the immediate region next to the colleges. Second, not all of these projects are marginal ones. In fact, we observe an increase on both tails of the project value distribution. Higher value projects seem to be linked to the ability of entrepreneurs to dedicate more effort to their ideas when the opportunity cost of time is

low. Overlapping slack time also appears to ease team coordination, leading to more team-based and more complex projects.

A key limitation of the paper is that the results are obtained from an idiosyncratic setting (crowdfunding) and population (college students). Within that setting, the estimated effects are large: 45% more projects are posted during breaks.²⁶ We are also only able to imperfectly measure project value and complexity, cannot identify when a team started working on an idea (because we only observe projects once they are posted on the platform), its exact stage of evolution, and where it stands between the ideation and commercialization stage. This limits the set of alternative explanations that we can rule out. For example, we are able to show that the increase in projects is not driven by more funds becoming available on the platform because students are on break. We also link breaks at schools with specific human capital (e.g., engineers, designers) to projects in the relevant categories on Kickstarter. Effects for breaks that are plausibly more exogenous and not scheduled (snow closings) also provide further robustness to the causal interpretation of the results. At the same time, while the model endogenizes effort allocation, in an ideal setting one would be able to measure not just the rate of innovation and effort, but also its direction; that is, are the projects posted when slack time is available fundamentally more risky and exploratory? Follow-up research with better data may be able to answer this question and to directly separate the role of idea shelving from execution. Deadlines may also play an important role in this context: for example, are breaks associated with more projects posted because they are finite and encourage students to make progress before work weeks start again? Are continuous blocks of time important because they allow individuals to focus without distractions? Given the constraints from the setting, we are unable to quantify the role of these alternative explanations.

Table 9. Effects of Increasing the Minimum Effort Level

Variables	(1) Projects ratio	(2) Projects ratio	(3) Funding ratio	(4) Funding ratio	(5) Large projects ratio	(6) Large projects ratio	(7) Team size ratio	(8) Team size ratio
<i>All breaks</i>	0.0000 (0.0002)	−0.0002 (0.0002)	0.0004 (0.0003)	−0.0006** (0.0003)	0.0002 (0.0002)	−0.0008*** (0.0002)	0.0006 (0.0005)	−0.0012* (0.0006)
<i>All school breaks after the change^a</i>		0.0006** (0.0003)		0.0024*** (0.0006)		0.0024*** (0.0006)		0.0045*** (0.0013)
Observations	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665
R-squared	0.025	0.025	0.014	0.015	0.002	0.002	0.019	0.019
Number of cities	10,091	10,091	10,091	10,091	10,091	10,091	10,091	10,091

Notes. For columns 1 and 2, the dependent variable is the ratio between the number of projects in the design and technology categories and the number of projects in all the other categories for a given city-week. The dependent variables of the other columns are similarly defined based on the total amount of funds, the share of projects with large target amounts (over \$30,000), and the share of team projects.

^aAfter the change^a indicates time periods after the May 2012 policy change. City and week fixed effects are included in all regressions. Robust standard errors are clustered at the city level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

That said, we interpret the empirical results as providing support for the insights of the theoretical framework. These insights are general and can inform policies targeted at encouraging innovation and experimentation within different types of organizations. Within an organization, one can broadly think of the breaks we study in the paper as periods of time where employees are not required to focus on short-run objectives, but are allowed to explore new ideas. Slack time can take multiple forms in such a context: on one extreme, it could be implemented in a way that is similar to an academic sabbatical, offering specific individuals the possibility to experiment with extremely risky and novel ideas for an extended period of time. Examples of this approach are “Skunkworks” projects, such as IBM’s “Project Chess” (in charge of the IBM PC), Steve Jobs’ secretive team of “pirates” working off campus on the first Macintosh (Isaacson 2011), and Google’s X Lab. On the other extreme, slack can be implemented as a flexible resource that employees can draw upon on a more regular basis as in 3M’s 15% time (which was responsible for the Post-It notes) or Google’s 20% time (which incubated Gmail and AdSense). Our results highlight that uninterrupted blocks of time are critical for developing high-potential ideas. In the absence of slack, projects that may have already absorbed time and resources through their ideation phase may never get developed further because teams cannot find the right time to execute on them. This challenge has been previously identified within the attention-based view of the firm (Ocasio 1997), and our paper builds on this view by examining how a critical, but understudied, component of managerial attention—time—influences the types of questions asked by innovative teams and the projects pursued. Slack time, by making routine priorities more versus less salient to managers and innovators, should be considered as an additional, key dimension of the “organizational context” that constrains and directs attention within a firm.

A key challenge for many organizational approaches to slack time is that radical new ideas may require coordination and resources that span the organization. The more complex the idea, the more likely that “overlapping slack” between team members with complementary skills and perspectives will be critical for its success. In the absence of overlap, teams may not be able to coordinate and iterate effectively on their initial concept to ensure momentum within the organization. Anecdotally, Google, which used to provide 20% slack time to its employees, recently restructured the policy as “Area 120.”²⁷ According to Google’s CEO, Area 120 “is giving people a chance at 20% time more formally” by offering them longer spells of continuous time (up to multiple months) and the possibility to build teams across the organization.

Last, in the absence of incentives targeted at cur-tailing low-quality contributions and introducing checkpoints in the use of slack time within an orga-nization, such policies can also induce a proliferation of low-value projects. This will likely lead to an ineffective allocation of resources, as productive individuals are moved away from their regular tasks to embark on bad projects. Companies interested in increasing experi-mentation and innovation through slack time need to therefore mitigate its negative effects with mecha-nisms targeted at preventing low-quality contribu-tions. In the case of LinkedIn’s [in]cubator program, not only are projects screened by top executives before entry but the company has also adopted a milestone-based approach to ensure the quality of projects at different stages in their evolution.²⁸ This replicates the model used by professional investors such as angel investors and venture capitalists to select startups and progressively increase resources as a team and idea’s true potential is revealed over time.

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Endnotes

¹ Crowdfunding is the practice of funding projects online by raising small amounts of money from a large number of people.

² Mollick (2014) provides an early study of the funding dynamics on crowdfunding platforms, and Agrawal et al. (2013) discuss key eco-nomic frictions from the viewpoints of both entrepreneurs and in-vestors. A key finding of the literature is that funding increases with accumulated capital. The crowd views accumulated capital as a signal of quality, and this may lead to herding (Zhang and Liu 2012, Kuppaswamy and Bayus 2013, Agrawal et al. 2015). One exception to this finding is that of Burtch et al. (2013), who show that public goods concerns can counteract herding effects. Mollick and Nanda (2016) examine the “wisdom of the crowd” and show that, overall, the crowd appears to select projects similar those of experts. Also related to this information, Burtch et al. (2015) show that privacy concerns play a role in funding decisions. Instead of informational issues, the paper focuses on the determinants of the supply of projects and their quality.

³ See details in Online Appendix A2. In an additional extension of the baseline model, we develop a two-period model in which projects arriving during the work period can be “shelved” until the break. This extension does not generate new predictions, but it is useful in interpreting the empirical results.

⁴ Because it is empirically impossible to identify different arrival rates, we normalize them to be the same across periods. Allowing for

different arrival rates affects only the first prediction because the other predictions are normalized statements. Intuitively, the arrival rate is likely to be higher during breaks, because there is more time to think about ideas. This would make the quantity of ideas developed during breaks even higher.

⁵ We use an exponential distribution, because it captures two features of the setting: that support is positive and that distribution is skewed to the low end (i.e., lower-quality ideas are more likely than higher-quality ones). Note that Prediction 1–3 do not rely on assumptions about the distribution.

⁶ The thresholds are determined by $\tilde{\pi}_w(q) = 0 \Leftrightarrow q\bar{c} - c_w \frac{q^2}{2} = 0 \Leftrightarrow \bar{q}_w = c_w \frac{2}{\bar{c}}$. Thus, $\bar{q}_0 < \bar{q}_1$ as $c_0 < c_1$.

⁷ The campaign data are obtained from Kickspsy, one of the top websites that monitors live Kickstarter activity over time. This data source is often used in papers studying crowdfunding, because it is comprehensive in terms of the variables it captures.

⁸ See <https://pando.com/2012/12/02/memoto-secrets-of-a-half-million-dollar-kickstarter-campaign/>.

⁹ See <http://colleges.usnews.rankingsandreviews.com/best-colleges/rankings/national-universities/data>.

¹⁰ In addition, the descriptive statistics show that the maximum number of successful projects for any U.S. city in a single week is 45 (Los Angeles, California), whereas the maximum number of failed projects is 79 (also Los Angeles). In a single week, cities are able to attract as much as \$21.8 million in successful funds, with an average per city-week of \$445 and a standard deviation of \$23,633.

¹¹ Other dependent variables include the total amount raised by the projects posted in city c during week t , project characteristics for all projects posted in city c during week t , such as the amount of effort invested into a project (description length, number of FAQs, and number of updates), the number of unique skills, and team size.

¹² Like with many other quasi-experimental regression papers (e.g., Athey and Stern 2002, Simcoe and Waguespack 2011), the R-squared in the analysis in this table is low. This is not surprising given that city fixed effects are differenced out rather than estimated and that there are many reasons people post projects on Kickstarter besides having time during college breaks. Key for our conclusions is that the co-efficient estimates have statistical power and magnitudes of economic importance.

¹³ Online Appendix Table A1 takes this one step further by pro-gressively dropping schools with the highest enrollment from our sample (moving from column 1, where all breaks are included, to column 4, where only breaks in schools with the lowest enrollment are in the sample). As can be seen from the table, the main effect is driven by breaks that affect the colleges with the largest enrollment. The online appendix instead explores the heterogeneity within a break and across breaks of different lengths. This allows us to see if most projects are posted right at the beginning of a break and how the length of a break influences our main effect.

¹⁴ The sample projects span the main 13 categories defined by Kickstarter, including art, comics, dance, design, fashion, film and video, food, games, music, photography, publishing, technology, and theater.

¹⁵ Notice that snow breaks, despite being unexpected, do not provide a good test for shelving, because they take place in the same context in which individuals might shelve projects in expectation of future breaks.

¹⁶ A caveat is that the exact impact of breaks on the quantity and quality of projects would be different with and without the ability to shelve projects. However, assigning a direction or magnitude to this difference is not obvious (see Online Appendix A3 for an extension of the baseline model that incorporates shelving).

¹⁷ We find the same results when further segmenting the distribution and allowing for more bins.

¹⁸Using Amazon Mechanical Turk, we also classified the content of project updates posted during breaks by break projects and updates posted not during a break by nonbreak projects. Break updates were more likely to discuss fundraising or thank the crowd for its support, to involve brainstorming or the discussion of ideas for the project, to cover a discussion of materials, inputs, manufacturing, and production (including filming and recording), and to update backers on shipping and estimated delivery time. Nonbreak updates were more likely to acknowledge a delay or discuss something else (although this second difference is small). We did not find any difference in how frequently the different sets of project updates discussed issues with the projects (other than delays).

¹⁹Given the same mean of the value distribution, the certainty-equivalent value (i.e., the payoff an agent would have to receive to be indifferent between a certain outcome and an uncertain one) of a risky project decreases with its variance. Thus, with lower development costs, a risk-averse entrepreneur would be willing to accept riskier projects that have lower certainty-equivalent values.

²⁰Despite the possibility that students spend their breaks visiting family or on vacation, the assumption that coordination costs are lower during breaks is reasonable, because in contrast to regular school weeks—in which all students are uniformly busy with schoolwork—the students interested in entrepreneurial projects are able to control their schedule more freely during breaks.

²¹This is based on whether a project is above or below the median in terms of complexity.

²²Whereas our measures for complexity are not perfect, for them to be problematic for the interpretation of the results, entrepreneurs working on projects during breaks would need to systematically include more skills in their bios—relatively to the ones they have—than entrepreneurs working during work weeks. If the measures are instead noisy, this would bias us against finding the hypothesized effects.

²³See <https://www.kickstarter.com/blog/accountability-on-kickstarter>.

²⁴See <https://www.kickstarter.com/blog/kickstarter-is-not-a-store>.

²⁵Columns 1 and 3 provide a baseline comparison between break and work periods for the relative number of projects (or the relative amount of total funds) in design and technology categories relative to all the other categories.

²⁶This large effect is plausible given the large number of students relative to the number of Kickstarter projects. In particular, a back-of-the-envelope calculation suggests that this increase amounts to 458 new projects per year, a small number relative to the over 4 million students enrolled in the top 200 colleges in the United States.

²⁷<http://www.forbes.com/sites/miguelhelft/2016/05/19/google-ceo-sundar-pichai-confirms-area-120-corporate-incubator/#409a3dc44f73>.

²⁸According to the company, ideas first must be developed as prototypes and clear two rounds of judging, where the final round is directly run by Founder Reid Hoffman and CEO Jeff Weiner. Given the stakes and visibility of these judging rounds, it is clear that employees have strong incentives to perform. Only projects showing promise at 30 days graduate to 60-day projects, and only those that have made sufficient additional progress at day 60 are allowed another 30-day extension. See <https://blog.linkedin.com/2012/12/07/linkedin-incubator>.

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