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Abstract

Traditional innovation models assume that new ideas are developed up to the point where the benefit of the marginal project is just equal to the cost. Because labor is a key input to innovation, when the opportunity cost of time is lower, such as during school breaks or time off from work, then such models predict that the number of ideas developed will be greater, but the average quality will be lower due to the lower expected value of marginal ideas. However, we posit that slack time such as school breaks may be qualitatively different than work time because contiguous blocks may be particularly beneficial for working on complex projects. We present a model incorporating this idea that predicts that although more ideas will be produced during slack time, they will have higher average complexity and perhaps even higher average value. Using data on 165,410 projects posted on Kickstarter (2009-2015), we report findings consistent with the model's predictions.

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"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

Companies and governments encourage innovation because it enhances productivity and competitiveness. However, innovation is costly. It requires time, effort, and resources. Yet, despite the cost, employees and students generate many innovations, including some that are outside the scope of work required by their job or school.

A simple economic model of innovation with a downward sloping demand curve and an upward sloping supply curve predicts an equilibrium level where the marginal benefit of one more innovation just equals the marginal cost of producing it. As such, it is not surprising that providing workers with more time by way of holidays or other forms of slack time could increase their level of innovation because a lower opportunity cost of time shifts the supply curve to the right, enabling workers to produce more innovations.

Such a model also predicts that the innovations generated as a result of additional slack time are lower quality than those produced in the absence of slack time. The slack time innovations should be, after all, the marginal ones. This raises a puzzle. Why do firms, such as Google, 3M, and Wella, firms that already provide innovation-oriented work environments for their employees, also provide slack time to encourage more innovation if doing so only facilitates the development of marginal ideas?

We conjecture that one reason might be that innovations facilitated by slack time are not necessarily of lower value. Instead, they are different than those developed during the normal course of work or school when people are busy. We develop a simple model to examine this. The model has two salient features. The first is that the opportunity cost of developing an innovation is higher during work time than during slack time. This feature alone produces the familiar predictions that slack time facilitates an increase in innovations, and that the marginal innovations are of lower

value.

However, the second feature is that the complexity of an innovation may disproportionately increase the cost of developing it during work time compared to during slack time because work time is more fractured. In other words, complex projects may be accomplished in less total time when performed using a contiguous block of time rather than in shorter segments. This may occur for two reasons. The first is focus. Research shows that interruptions can reduce performance in complex tasks. Whereas Becker (1965)'s traditional theory of time allocation did not consider the role of time blocks in the household production function, more recently Wolff and Makino (2012) have extended his original model to account for non-constant returns (i.e., by incorporating the idea that utility may differ between a certain activity being performed over multiple, smaller chunks of time versus a contiguous block). The authors find empirical support for their assumption using the 2007 extension of US Daylight Saving Time as a natural experiment. In addition to this "fixed-cost" explanation, there is a robust literature documenting that interruptions can reduce performance in complex tasks, particularly in clinical settings (Coiera 2012). For example, interruptions lead to unfinished tasks (Westbrook, Coiera, Dunsmuir, Brown, Kelk, Paoloni, and Tran 2010), poorly executed tasks (Foroughi, Werner, Nelson, and Boehm-Davis 2013), and an increase in mistakes (Cellier and Eyrolle 1992). Research has also shown that an extended period of time can increase creative output (Katz and Allen 1985), perhaps due to the role of flow (Csikszentmihalyi 1997). Second, for projects developed in teams, a contiguous block of time during which all participants have more flexible schedules may facilitate coordination among collaborators.

Introducing a complexity penalty for developing innovations during work time compared to during slack time leads to the prediction that not only will slack time lead to more innovations, but that those innovations will be on average more complex. Furthermore, depending on the relative size of the complexity penalty relative to the difference between the opportunity cost of time during work versus during breaks, innovations produced during slack time may be more valuable on average, not less as traditional models imply.

Thus, we develop a model that distinguishes between high versus low opportunity cost of time to distinguish innovating during work time versus during break time. The model also incorporates

a penalty that increases with the complexity of the innovation for projects conducted during work versus break time. The model delivers three predictions. First, the probability of developing an idea is higher during break time than during work time. Second, the average complexity of developed ideas is the same for break time as it is for work time if there is no complexity penalty, but is greater for ideas developed during break time when there is a penalty. Third, the average value to the funders of ideas developed during work time is higher when there is no penalty, but the reverse is true if the complexity penalty is high enough.

We test these predictions using data on innovation as measured by projects posted on Kickstarter, a crowdfunding platform.[1] These projects represent innovations across a broad range of categories, such as design, technology, music, and fashion. We focus on the step of the innovation process associated with posting a project to the platform. While specific posting details are unique to this setting, the general requirement of preparing materials to communicate the vision and plan for developing an idea in order to gain support and attract resources is common to most innovation environments, from early stage entrepreneurship to corporate settings.

Specifically, we measure the location and timing (i.e., city-week) of all new projects launched on Kickstarter between April 2009 and April 2015. Kickstarter is the largest rewards-based crowdfunding platform in the world in terms of both the number of projects posted and the amount of capital transacted. We combine these data with information on the exact timing of school breaks in locations with top US colleges. We use school breaks as our measure of slack time.

The first prediction of the model is that the number of projects posted during break weeks will be higher than during work weeks. The results are consistent with this prediction: We document a sharp rise in posting activity in weeks during college breaks, controlling for differences across time using week fixed effects and differences across locations using city fixed effects.

Furthermore, our results are strongly suggestive of a causal relationship between college breaks and the number of projects posted. We observe no pre-trend, either positive or negative, in the number of projects posted before students are on vacation. The lack of a positive pre-trend suggests

[1] Crowdfunding is the practice of funding a project by raising small amounts of money from a large number of people by leveraging a digital platform. It is a form of early stage capital for many technology companies and it has become an important source of funding for the arts (Agrawal, Catalini, and Goldfarb 2013, Mollick and Nanda 2014, Belleflamme, Lambert, and Schwienbacher 2014).

that the result is not driven by an omitted variable that is coincident with the timing of school breaks in college towns. The lack of a negative pre-trend suggests that projects posted during breaks are not simply shifted in time from the weeks leading up to the break. This is an important point. The lack of a pre-trends suggests that the additional projects posted during breaks would likely not have occurred at all in the absence of a break. To the extent that each project represents an entrepreneurial experiment, the counterfactual absence of these experiments would likely translate into a significant loss to the economy (Kerr, Nanda, and Rhodes-Kropf 2014).

Providing additional support for the causal interpretation that slack time drives innovation, we report evidence showing that the increase in projects posted is consistent with the expertise of the students affected: when top engineering schools are on break, we see a positive effect on technology projects but not art projects, and vice versa when art and design schools are on break. Furthermore, we report results suggesting that the increase in postings is driven by the supply side (projects by entrepreneurs) rather than by increased capital availability due to students allocating funds while on break. We do this by documenting that the result does not hold for projects started just before a break where fundraising continues during the break. We also examine days when universities are closed for snow, providing an exogenous increase in slack time. More projects are posted on snow days. Furthermore, years with more snow days have more projects, controlling for city and year fixed effects.

Therefore our results support the first prediction of the model: More ideas are developed into projects during slack time. We turn next to the perhaps more intriguing hypothesis that projects posted during breaks may be different than those posted during work time.

The second prediction of the model is that slack time enables more complex activities, assuming that there is a benefit from contiguous time (i.e., this is a result of the complexity penalty for pursing complex projects during work time). We examine two distinct types of complexity: complexity in implementation and complexity in team coordination. In terms of the latter, we find that projects posted during breaks have larger teams.

In terms of implementation complexity, we use two different measures. First, we show that the promised delivery date is longer for projects posted during breaks, suggesting that slack time

projects are more complex on average.[2]

Second, and more directly, we explore a change in Kickstarter's policy that increased the complexity of posting a project in two of Kickstarter's thirteen categories. The policy change was implemented by Kickstarter in response to a series of inexperienced inventors who attracted significant capital for their projects, and then failed to deliver as a result of manufacturing and distribution issues linked to inadequate planning. Because many of these problems were often foreseeable to those with consumer product manufacturing experience, the site required that projects in the Design and Technology categories provide an explicit manufacturing plan and a prototype. This substantially increased the complexity of the requirements for posting. Using a difference-in-differences approach where we compare the two treated categories to the other eleven categories before versus after the policy change, we find that, after the policy change, slack time has a disproportionately positive effect on the number of projects posted during college breaks in the treated categories relative to the others. Thus, an increase in complexity led to a disproportionate increase in the number of projects posted in the treated categories during breaks.

The third prediction is that ideas produced during slack time will be more valuable if the benefit from contiguous time is high enough. While value is difficult to measure precisely, we use funding goal size as a proxy for the expected value. Technology and Design projects had higher goals during breaks after the policy change. Furthermore, throughout the sample, goal size is larger during breaks for projects that achieve their funding goals. We interpret these results as consistent with a significant benefit to contiguous development time.

Team size, time to delivery, and goal size are inter-related: Projects with a longer delivery time tend to involve larger teams and ask for a larger goal. We show that even conditioning on two of the three, the other tends to be higher during breaks. For example, for projects with large goals and long delivery times, the teams are larger during breaks. We interpret this to suggest that while each measure is an imperfect proxy for complexity and/or value, together the results are consistent with the prediction that projects posted during break weeks are qualitatively different than projects posted during work weeks.

[2]Backers on crowdfunding platforms prefer shorter delivery dates, and typically only more complex projects are able to post longer delivery windows and still be funded.

This paper links the nascent but rapidly growing literature on crowdfunding to the more established literature on innovation. Thus far, the crowdfunding literature has focused on issues related to asymmetric information between funders and project entrepreneurs. Agrawal, Catalini, and Goldfarb (2013) review much of the literature and discuss the incentives and disincentives of crowdfunding from the points of view of entrepreneurs and financiers. Entrepreneurs gain access to inexpensive capital and feedback. In exchange, they must disclose their ideas and manage the crowd. Financiers receive early access to products and a formalization of contracts for things they might have supported by donation. Similarly Belleflamme, Lambert, and Schwienbacher (2014) emphasize asymmetric information in their review. Broadly, entrepreneurs and financiers are initially overoptimistic about outcomes (Mollick 2014), though overall the crowd appears to select similar projects to experts, at least in theatre (Mollick and Nanda 2014). Perhaps the dominant finding in 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 (Agrawal, Catalini, and Goldfarb 2015, Zhang and Liu 2012, Kuppuswamy and Bayus 2013). One exception to this finding is Burtch, Ghose, and Wattal (2013), who show that public goods concerns can counteract herding effects. Also related to information, Burtch, Ghose, and Wattal (2015) show that privacy concerns play a role in funding decisions.

Our emphasis here is different. Instead of focusing on challenges related to asymmetric information, we focus on the decision to make the effort to post an innovative project for crowdfunding at a particular time. We examine how this decision relates to the opportunity cost of time. In this way, our work is perhaps more directly related to Davis, Davis, and Hoisl (2014)'s research on the difference between leisure time invention and work time invention. They demonstrate that leisure time inventions tend to be less science-based and smaller. Our research also relates more generally to the broader literature on the benefits and costs of slack time in organizations (Nohria and Gulati 1996, Menzel, Aaltio, and Ulijn 2007, Richtner, Ahlstrom, and Goffin 2014).

Our measure of innovation, posting a project on a crowdfunding site, reflects a single step in the multi-step innovation process. What are we actually measuring? Most likely the main variation in our measure of innovation is driven by variation in the cost of preparing materials required for

posting a project on the crowdfunding website, rather than variation in the cost of developing the idea itself. Many of the ideas posted are embryonic at the time they are posted on the platform. However, in order to attract funding, the entrepreneur must communicate the innovation through text and often a video and also develop a reward scheme. The policy change described above provides the most direct measure of a change in the cost of preparing materials required for posting a project. So, one view is that our empirical results are informative about complexity associated with the mundane (i.e., non-creative) tasks associated with preparing the materials to pitch an innovation. A broader interpretation is that our measure incorporates the time and effort required to partially develop the innovation itself (as the policy change introduced the requirement for a working prototype). Both interpretations are consistent with the model.

We proceed by first presenting the formal model that yields our three predictions. We then describe the data and empirical setting. With this background, we test each of the predictions of the model in turn. We conclude with a discussion of the implications of our results for organizations focused on enhancing innovation.

2 Theoretical Model

We develop a simple model to explore the quantity and type of projects that are developed during break weeks (B) and work weeks (W). The two week types differ on two dimensions: 1) the opportunity cost of time is lower during break weeks; 2) an idea arriving during a work week is developed using spare time (e.g., an hour every day), whereas an idea arriving during a break week is developed using a concentrated block of contiguous time. The model focuses on project development given an idea; the idea generation process is exogenous. This is appropriate to our empirical setting in which we observe the precise timing of a particular stage in the innovation process.

One idea arrives in each period. An idea is characterized by two parameters: (1) the ex-ante value at the time of its arrival, q; and (2) the complexity of the idea, k.[3] Let the overall value of

[3]Empirically, as mentioned above, we examine two types of complexity: difficulty coordinating between multiple team members, and difficulty developing the idea into a project.

an idea be q if the idea arrives during a break, and $e^{-\beta k}q$ if it arrives during a work week, where $\beta \geq 0$.[4]

The scaling factor, $e^{-\beta k} \leq 1$, captures the relative downside of not being able to use a contiguous block of time to develop the idea.[5] There are two distinct reasons why a contiguous block of time may be beneficial for developing complex projects. First, developing and executing on a complex idea may benefit from the ability to focus on the idea for a contiguous block of time. Thus, the contiguous block of time available during breaks may enable higher quality execution of a complex process. Second, for projects that involve teams, a contiguous block of time in which all participants have more flexible schedules should facilitate coordination among collaborators. Thus, a school break in which all students have no classes should make it easier for students to find time to meet and move the project forward.

For simplicity, we assume that q and k follow uniform distributions, $U[0, 1]$. Furthermore, we assume that they are independent of each other. Moreover, we assume that the complexity penalty that applies during work weeks (but not break weeks) increases with the level of complexity (i.e., $e^{-\beta k}$ decreases with k).

Let the development cost required before posting an idea be c_B and c_W for break weeks and work weeks, respectively. To highlight the difference in opportunity cost of time, assume $c_B < c_W$. Finally, assume that $e^{\beta} c_W < 1$, which guarantees that some projects will be developed even for very high levels of complexity (i.e., when $k = 1$).

[4]When an idea that is sufficiently complex arrives during a work week, the innovator may shelve the idea and wait until she has a block of time. Such shelving would exaggerate the magnitude of the impact of the break, though not change the general conclusion that projects developed during breaks are qualitatively different. Empirically, we do not observe a pre-trend. Therefore, our results are not consistent with shelving, at least in the short term.

[5]If spare time during work weeks was more beneficial than a contiguous block of time during break weeks for the overall value of an idea, then we would have the following predictions. First, the probability of developing an idea arriving during the break can be lower than that during a work week when the relative benefit is sufficiently large. Suppose that the overall value of an idea during a work week is δq and that $\delta > 1$. Then, an idea is developed if $q \geq \frac{c_W}{\delta}$. This threshold can be lower than that for the break when δ is sufficiently large because it decreases with δ while q_B^* is not a function of δ. Second, the expected value of ideas developed during work weeks is higher than that during the break (similar to Prediction 3, we can show that the average expected value of ideas developed during work weeks is an increasing function of δ. Thus, when $\delta > 1$, the expected value of developed ideas is greater than that when $\delta = 1$, which is, in turn, higher than that for ideas developed during the break). As we will see, this second prediction is inconsistent with our results.

Thus, the expected payoff from developing an idea that arrives during a break week is

$$U^B(q) = q - c_B, \tag{1}$$

and for a work week is

$$U^W(q, k) = e^{-\beta k} q - c_W. \tag{2}$$

Note that equation (2) is different from (1) in two ways: first, the opportunity cost of time is higher; and second, the value of an idea is scaled by $e^{-\beta k}$.

In the following, we consider the case of $\beta = 0$ and the case of $\beta > 0$ separately. When $\beta = 0$, the only difference between the two periods is the opportunity cost of time. Thus, the quality threshold above which an idea is developed is higher for work periods, and quality thresholds for both periods are independent of k. When $\beta > 0$, ideas arriving during a work week become less valuable because of the lack of a contiguous block of time for development. This makes the threshold in ex-ante quality q even more stringent. Denote the quality threshold for the break as q_B^*, and that for work weeks when $\beta = 0$ as $q_{W,\beta=0}^*$, and that for work weeks when $\beta > 0$ as $q_W^*(k)$. The following proposition summarizes how the thresholds compare, and the results are illustrated in Figure 1 using a numerical example.

Proposition 1. *$q_B^* < q_{W,\beta=0}^* \leq q_W^*(k)$, and $q_W^*(k)$ increases with k.*

Proof. It is straightforward from Equation (1) and (2) that $q_B^* = c_B$, $q_{W,\beta=0}^* = c_W$, and $q_W^*(k) = e^{\beta k} c_W$. $q_W^*(k)$ increases with k because $\beta > 0$. □

Proposition 1 generates the following predictions on the quantity and type of projects developed in different period types. Prediction 1 is straightforward from Figure 1.

Prediction 1 (Probability of development)**.** *The probability of developing an idea is higher during breaks.*

When there is no comparative advantage in developing ideas using a contiguous block of time (i.e., $\beta = 0$), complex ideas that arrive during work weeks will not be screened out; otherwise,

given any ex-ante quality q, ideas that are sufficiently complex will not be developed because the eventual value is too low to justify the development cost.

Prediction 2 (Average complexity of developed ideas)**.**

(a) When $\beta = 0$, the average complexity of developed ideas is the same for break weeks and work weeks.

(b) When $\beta > 0$, the average complexity of developed ideas is higher during break weeks.

Proof. When $\beta = 0$, the quality thresholds are independent of k for both period types and, thus, the average complexity of ideas developed is $\frac{1}{2}$ in both work and break weeks. When $\beta > 0$, given q, only ideas with $k \leq k^*(q)$ are developed, where $k^*(q)$ is such that $U^W(q, k^*(q)) = 0$ if $q < e^{\beta} c_W$, and 1, otherwise. Thus, the expected complexity of ideas developed during a work week is $E_q[E_k[k|k < k^*(q)]|q \geq q^*_W(k)] = E_q[\frac{1}{2}k^*(q)|q \geq q^*_W(k)] < \frac{1}{2}$. □

When there is no comparative advantage in developing ideas using a contiguous block of time (i.e., $\beta = 0$), the overall value of developed ideas is higher during work weeks since the quality threshold is higher. When $\beta > 0$, the ultimate value of an idea suffers because of the disadvantage of only being able to use spare time during the work week. When spare time is sufficiently less effective than a contiguous block of time (i.e., when β is sufficiently large), the average value of ideas developed during work weeks is lower despite the opportunity cost of time being lower during breaks (see Figure 2).

Prediction 3 (Average value of developed ideas)**.**

(a) When $\beta = 0$, the average value of ideas developed during work weeks is higher.

(b) When $\beta > 0$, the average value of ideas developed during work weeks is lower than during break weeks if β is sufficiently high.

Proof. When $\beta = 0$, the expected value of ideas developed is $E_q[q \geq q^*_B] = \frac{1+c_B}{2}$ during a break, which is lower than that for work weeks, $E_q[q \geq q^*_W] = \frac{1+c_W}{2}$.

When $\beta > 0$, the expected value of ideas developed during work weeks is

$$E_k[E_q[e^{-\beta k}q|e^{-\beta k}q - c_W \geq 0]] = \frac{1}{2}(\frac{1 - e^{-\beta}}{\beta} + c_W),$$

which monotonically decreases with β. This is because the derivative of $\frac{1-e^{-\beta}}{\beta}$ with respect to β is $\frac{e^{-\beta}(1+\beta)-1}{\beta^2}$, which is negative because $e^{\beta} > (1+\beta)$ (and, hence, $\frac{1+\beta}{e^{\beta}} < 1$) for any $\beta > 0$. Thus, the expected value of ideas developed during work weeks is lower than that of ideas developed during break weeks when β is sufficiently large (that is, when $\frac{1-e^{-\beta}}{\beta} < 1 + c_B - c_W$). □

We now turn to our data to test the predictions of the model.

3 Data and Empirical Setting

Our empirical setting is Kickstarter, the world-leading reward-based crowdfunding platform. We collect data for the 165,410 US-based projects that attempted to raise money on the platform between April 2009 and April 2015. We have information on approximately $1.4B raised both by successful (44% of the projects, 89% of the capital) and failed projects (56% of the projects, 11% of the capital). The distribution of capital is highly skewed: the top 1% (10%) of projects accounts for $590M ($1B), or 42% (76%), of the capital (Agrawal, Catalini, and Goldfarb 2013).

Our data contain project-level information that is publicly available on Kickstarter. This includes information on the time each project was posted, total funds raised, and descriptive information about each project. We do not have comprehensive data on the timing of funding within projects nor the location of the funders.

We define success and failure relative to the funding goals of the campaign. Specifically, Kickstarter requires projects to state a funding goal in advance. Entrepreneurs that start projects that fail to achieve their funding goal do not receive any money. Instead, the capital is returned to funders. We label projects that achieve their funding goal as "successful" and ones that do not (and therefore do not receive any funds) as "failed." The overall success of projects, once funded, is not our focus here and has been studied elsewhere (Mollick and Nanda 2014).

The projects span the main 13 categories defined by Kickstarter (Art, Comics, Dance, Design, Fashion, Film & Video, Food, Games, Music, Photography, Publishing, Technology, Theater), and 10,091 US cities and towns.

We manually collect data on school breaks between 2009 and 2015 (summer break, spring break,

winter break, Thanksgiving, reading week, snow days) for the top 200 US colleges as defined by US News & World Report.[6] This information is publicly available through posted academic calendars. We consider a location to have a school break in a given week if a top 200 college within five miles of the city centre has a break that week. We also manually collected data on snow days from school websites, twitter, and other online news reports.

In Table 1, we present descriptive statistics at the city-week level for our main sample. During our 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 other words, in most city-weeks, no projects are launched. However, the distribution is right-skewed with many zeros, such that some cities have projects posted in many weeks.

In addition, the descriptive statistics show that the maximum number of successful projects for any US city in a single week is 45 (Los Angeles, CA), whereas the maximum number of failed projects is 79 (also Los Angeles). In a single week, cities are able to attract as much as $21.8M in successful funds, with an average per city-week of $445 and a standard deviation of $23,633. Approximately 3.5% of our observations are city-weeks where at least one of the top 200 colleges is on school break, the majority of it being summer break weeks (2% of the sample), followed by winter breaks (0.75% of the sample) and spring breaks (0.35% of the sample).

Our model yields predictions about projects that are more likely to benefit from a contiguous block of time. We discuss two types of project complexity that might yield such benefits: Coordination costs among team members and interruption of difficult tasks. We use a straightforward measure for coordination costs: number of listed team members.

Measuring project difficulty is more challenging. We use two distinct measures. First, we leverage a May 2012 change in Kickstarter's posting requirements for Design and Technology projects. Both before and after the change, posting a project involves a variety of tasks, even if the entrepreneur has fully developed their idea. Entrepreneurs must prepare a detailed description of their idea and many also illustrate their idea through a short video (2-3 minutes). This involves describing how the creation works, the progress to date, and a project timeline. In addition, en-

[6]Source: http://colleges.usnews.rankingsandreviews.com/best-colleges/rankings/national-universities/data (accessed September 2013).

trepreneurs must estimate a budget for completing their project and describe line items in the budget. Also, on reward-based crowdfunding platforms including Kickstarter, the entrepreneur must design a schedule of rewards that are a function of the amount of money provided by the funders. The entrepreneur must also determine a financial goal (how much they aim to raise), which is not an arbitrary number because if they fail to raise that amount then they receive none of the money that they raised. However, they are able to raise more than the amount specified. Entrepreneurs must select the length of their fundraising campaign (60 days maximum) and must develop a plan for promoting their project to funders, which may include an email campaign to the network, individual follow-up emails, pitching to the press, social media activity, and possibly hosting offline events.

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 scope of the tasks required for posting projects in those two categories. One of the primary criticisms was that in most of these cases the entrepreneur raised capital and promised funders a product without any experience or preparation for production or distribution. Therefore, in May 2012 Kickstarter revised their rules to address accountability concerns, explain in a note that they now require entrepreneurs 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."[7] 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 for posting.[8]

In summary, the change disproportionately increased the complexity of tasks required to post Design and Technology projects to the platform, such as preparing a manufacturing plan, building a working prototype, and describing them clearly on the site.

As a second measure of project complexity, we use the expected wait time to receive the reward

[7]https://www.kickstarter.com/blog/accountability-on-kickstarter (Accessed on March 12, 2015)
[8]https://www.kickstarter.com/blog/kickstarter-is-not-a-store (Accessed on March 12, 2015)

(averaged for the location-week) because more difficult projects are likely to require more time to complete. This measure captures the expected complexity of actually completing the project, which is likely related to the complexity of the pre-posting development process, including describing and posting the project.

Our model also yields predictions about the value of projects. We use target goals as a proxy for value. Of course, these measures are necessarily imperfect proxies for complexity and value. We discuss the strengths and weaknesses of each in the Results section.

Kickstarter is widely used in many college towns. For example, Boulder, Provo, and Ann Arbor are all in the top 10 places for technology projects per capita. In light of the prominence of locations with colleges on Kickstarter, our empirical analysis exploits the week-by-week variation in slack time in these places. In particular, we examine correlations between school breaks and new projects on Kickstarter.

4 Empirical Strategy

We test the three predictions of the model with a straightforward econometric framework at the city-week level. We focus on a linear model with fixed effects to document the underlying correlations in a direct and easily interpretable manner. We exploit variation across cities in the timing of school breaks at local colleges and universities to estimate how the availability of contiguous blocks of time for college students influences the number and type of projects posted as well as the amount of funding they attract:

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

where Y_{ct} is either the number of projects posted on the platform in city c during week t or the total amount raised by the projects posted in city c during week t. In some specifications, Y_{ct} is a continuous variable such as the average time backers have to wait for a specific reward, the average number of team members on a project, or the average target amount for projects posted in the specific city-week.

Kickstarter identifies a city for each project, based on the location of the project entrepreneurs.

We use these as a measure of location. It provides a smaller geographic measure than a CBSA and a larger one than a Census Place. The key advantage is that it does not involve location aggregation or disaggregation of the core dependent variable. $CollegeBreak_{ct}$ is a dummy equal to one if any of the colleges in the focal city is on break in the focal week and zero otherwise. μ_c is a city fixed effect to control for underlying differences across US cities that are consistent over time. ψ_t is a week fixed effect to control for changes in the Kickstarter environment over time, and ϵ_{ct} is an idiosyncratic error term. The fixed effects mean that our analysis examines the change in the propensity to post projects and attract funding over time for cities where we observe at least one project. 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. Since nothing changes, we focus on the more parsimonious specification and do not include additional covariates. The fixed effects completely capture cities in which we never see activity, and thus we remove them from the analysis without any empirical consequences. In some specifications, we interact the $CollegeBreak_{ct}$ variable with time and market characteristics. Robust standard errors are clustered at the city level.

5 Results

We build our main result in three steps. First, we provide evidence in support of Prediction 1 (i.e., the probability of developing and posting an idea is higher during breaks). Specifically, we document that crowdfunding activity increases during breaks, both in terms of the number of projects posted and also the amount of funding raised (Section 5.1).

Second, in Section 5.2, we provide support for the causal mechanism implied in Prediction 1. In particular, we provide evidence of a causal relationship from college breaks to new crowdfunding projects in four ways. First, we show that the correlation between crowdfunding and college breaks is sharply confined to the timing of breaks without positive or negative pre-trends. This timing is not consistent with underlying time trends driving the results nor is it consistent with people waiting for the break in order to post projects. Second, we show that the types of projects observed make sense given the locations: Technology projects increase in locations with technology schools

and art projects increase in locations with arts schools. Third, we show that the result is likely not driven by a change in the supply of capital available to students during breaks: Projects posted just before a break do not attract disproportionate funding during break weeks. Fourth, and finally, we show that the results are similar for closures due to snow days, an unanticipated increase in contiguous time. In the aggregate, in years with more snow days we see more projects posted, suggesting that breaks lead to an increase in total projects posted and not merely a reallocation of projects across time.

In the last step, in Section 5.3, we directly test the remaining predictions of our model: That more complex and higher value ideas are developed during breaks. We first show that projects posted during breaks are more likely to have multiple team members, and therefore require more coordination. We also show a disproportionate increase in projects posted during breaks after the requirements for posting become more complex. Furthermore, we show that projects posted during the break are likely to be more complex in that they have longer development times (as proxied by the timing that the rewards are offered to backers). Finally, we show that projects posted during breaks are potentially higher value in that they are more ambitious (as proxied by their target amount, particularly for successful projects).

5.1 Prediction 1: More Ideas Posted During Breaks

In Table 2, we present our evidence in support of Prediction 1: when college students are on break in a city, more projects (Column 1) from that city are posted on Kickstarter and more funding (Columns 2 and 3) flows to projects in that city, controlling for week fixed effects and city fixed effects.

In Column 1, we show with 99% confidence that the number of crowdfunding campaigns launched increases during school breaks. The estimated coefficient, 0.030, is large relative to the average number of campaigns per city-week, 0.052 (Table 1, first row).

In Column 2, where we use funding (not logged) as the dependent variable, the estimated coefficient on school breaks is also positive and large relative to average values but is not significantly different from zero. This is a result of the highly skewed distribution of funding since the amount

raised in most city-weeks is zero or a nominal amount (mean value is \$445) but is occasionally very high (up to \$21.8 million). Therefore, to address concerns related to skew, in Column 3 we use $log(funding+1)$ as the dependent variable. Column 3 reports a positive and significant correlation between funding and college breaks.[9]

5.2 Evidence For a Causal Interpretation

The model underlying Prediction 1 implies that the correlation between projects and breaks is causal. We next provide four distinct pieces of evidence to support a causal interpretation.

In terms of timing, we explore the presence of a pre-trend in the data by introducing dummies for the weeks before and after a college break period in our main specification. In Figure 3, the baseline is any week more than 5 weeks away from a college break, and the coefficient estimated for t=0 reflects the average effect of all school breaks on crowdfunding activity in the focal city. The regression includes city fixed effects as well as week fixed effects, and the dependent variable is the total number of projects posted in the focal city-week. Estimated coefficients reflect the level of activity for the 5 weeks before, during (t=0), and 5 weeks after a break. As we illustrate in Figure 3, breaks are correlated with a substantial spike in crowdfunding activity. However, there is no *increase* in projects immediately before or after, ruling out a spurious correlation related to seasonality. Furthermore, there is no *decrease* in activity immediately before or after the break, suggesting that the observed increase in activity is not caused by shifting from immediately adjacent periods. If slack time during breaks merely leads entrepreneurs to shift *when* they post their project, then an increase in projects posted during break weeks would be coupled with a decrease in projects posted during work weeks. Furthermore, if entrepreneurs face a discount rate (they prefer receiving funding sooner rather than later), then weeks that are adjacent to the breaks would have a sharper drop in postings than weeks that are farther away. Thus, under the assumption of time discounting, if slack time shifts projects that would have been posted anyway, then we would expect a particularly

[9] As with many other quasi-experimental regression papers (e.g., Athey and Stern (2002) and 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 why people post projects on Kickstarter besides having time during college breaks. Key for our conclusions is that our coefficient estimates have statistical power and magnitudes of economic importance.

sharp decline in the weeks immediately preceding and following the slack period. However, we do not see such a decline in Figure 3. Thus, consistent with Prediction 1, we interpret these data as implying that breaks generate new project postings.[10]

Table 3 shows three further tests supporting our interpretation of a causal relationship. In columns 1 and 2 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 exploit 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 activity (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, we only use projects in the arts and in Column 2 we focus on projects in technology. 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 our expectation that technical orientation plays a key role in these types of projects.

If breaks provide college students with more time to browse through Kickstarter and fund projects they are interested in, including those by local entrepreneurs, then this will increase the supply of capital available to Kickstarter projects in college towns. Alternatively, if breaks give students more chance to ask for funds from family, again, this will increase the supply of capital. To assess whether the results are driven by an increase in the supply of capital, we examine the timing of funding associated with projects posted in the week preceding a break. We examine whether funding for those projects increases 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 expect to observe an increase in funding during break weeks for projects posted just prior to the break. However, in Columns 3 and 4 of Table 3, we report results indicating that funding

[10]To be clear, our model and interpretation do not require no shelving of projects and no anticipation of breaks. Rather, our interpretation requires that at least some projects would not have been produced in the absence of the break. The empirical finding of no shelving in the short run suggests that shelving (over the short run) is not a key factor in our data. Using annual variation in snow days, we also directly test for an increase in projects at the annual level below.

associated with projects started during a work week does not rise during break weeks even though fundraising efforts continue during those weeks.

Our fourth and final piece of evidence supporting a causal relationship examines unexpected college closings due to heavy snow. Column 5 of Table 3 shows that the effect of unanticipated closings due to snow is similar in magnitude to the effect of anticipated closings due to school breaks. By focusing on a set of breaks that are not pre-planned, this analysis further supports the interpretation that our results are not driven by delaying posting of near-complete projects until anticipated breaks.

Column 6 shows that snow days increase the number of projects posted overall. In other words, it is not that projects that would have been done outside of breaks now get completed during breaks. In particular, column 6 uses the city-year as the unit of observation and regresses the number of projects in a city-year on the number of snow days in that city-year. Given that the number of days that a college cancels class varies exogenously from year-to-year and city-to-city, the positive and significant coefficient suggests that such random increases in slack time have a positive causal impact on the number of projects produced.

Combined, we interpret this evidence to suggest that breaks cause more projects to be posted on Kickstarter, which supports the first prediction of our model.

5.3 Project Complexity and Value

The model generated two additional predictions. We explore each one in turn.

5.3.1 Prediction 2: Project Complexity

Prediction 2 follows directly from the assumption about the value of contiguous time. The model separates complexity (k) from ex-ante value (q), and Prediction 2 focuses on complexity. Specifically, the model predicts that more complex ideas will be developed during breaks when there is a complexity penalty associated with work weeks characterized by interrupted time ($\beta > 0$). In contrast, if there is no penalty, then the average complexity of ideas will be the same for break weeks and work weeks. This yields a direct empirical test of the sign of β (i.e., is contiguous time

more beneficial for more complex ideas?). If we see more complex ideas during breaks, then this suggests $\beta > 0$.

As mentioned above, team size is a measure of complexity in terms of coordination costs. During breaks, the somewhat complex task of coordinating between multiple team members is reduced because team members are likely to have more open schedules. Figure 4 uses information contained in the biographies of entrepreneurs to identify how many team members are behind a specific project: in the raw data, projects posted during the breaks have on average 0.5 more team members than projects posted during work weeks. Results are similar when controlling for city and week fixed effects. Figure 5 estimates a similar model to Figure 3, but with average team size as the dependent variable. There is a tangible increase in the average number of team members during breaks. This is consistent with the interpretation that break weeks enable more complex projects.

An alternative way to conceptualize complexity is the difficulty of getting the project ready for posting. As mentioned above, we use two distinct strategies to assess the relationship between slack time, difficulty of getting the project ready for posting, and the act of posting. First, we leverage the May 2012 policy change for Design and Technology projects at Kickstarter that increased the effort associated with development tasks that need to take place before posting to the site, such as preparing a manufacturing plan and building a working prototype. Therefore, we expect the complexity of posting Technology or Design projects to rise after this change. Prediction 2 suggests that, if there is a complexity penalty for work weeks (that is, $\beta > 0$), the policy change will lead to a decrease in the rate of posting these projects during work weeks compared to during break weeks.

Columns (1) to (4) of Table 4 report regressions of the share of projects in Technology or Design on breaks and the interaction of breaks with the change in policy. The results indicate that after the policy change, breaks are associated with a disproportionate increase in the proportion of projects posted in Design and Technology relative to all other categories. We interpret this as consistent with the idea that contiguous time plays a key role in the development of ideas of higher complexity, thereby providing further evidence that the data are consistent with Prediction 2 with $\beta > 0$.

Our second measure of project difficulty is the wait time between the posting of a project on Kickstarter and the expected delivery time of the rewards associated with it. While this measure is less direct, we show these results because they provide an additional way to explore our prediction. Since funders are likely to prefer shorter wait times (all else equal) and more difficult projects likely take longer to complete, we interpret longer wait times to be positively correlated with more complex implementation, and perhaps in turn more complex communication of the idea. Figure 6(a) shows that the average wait time between posting and the expected delivery of the first reward increases sharply during breaks. As in the previous figure, we do not observe a pre-trend nor a decay in the estimated coefficient in the weeks before and after the break. This increase during the break is consistent with Prediction 2 with $\beta > 0$: Complex projects are more likely during breaks. In Figure 6(b), we show robustness to the time between posting and the expected delivery of the last reward because projects may list more than one reward.

5.3.2 Prediction 3: Project Value

Prediction 3 states that the average value of ideas developed during break weeks will be lower than during work weeks if there is not a significant complexity penalty for work weeks (i.e., if β is low). However, if contiguous time is sufficiently useful, or the complexity penalty is high for work weeks (i.e., if β is high enough), then the value of ideas developed during breaks can be higher. In other words, the model highlights two opposing forces: break weeks are low opportunity cost time such that marginal projects will be developed, lowering the average potential value; however, break weeks also provide contiguous time, meaning that projects developed during break weeks may have higher realized value.

Next, we examine which of these two opposing forces dominates. We know that the results of our empirical analysis of Prediction 2 suggest that contiguous time has some benefit, formally that $\beta > 0$. Here we explore whether β is sufficiently high so that projects generated during breaks are at least as valuable as projects generated at other times, overcoming the difference potentially induced by low opportunity cost.

In order to measure the value of the project, we look at the average target amount of funding.

We interpret a higher target to suggest more anticipated value. If the project successfully raises funds, then it suggests that the market of funders agrees that the value was not over priced. Thus a higher target for successful projects suggests that the realized value of the project (to the project entrepreneur) is higher. As in prior figures, Figure 7 shows week-to-week coefficient values around school breaks. Here the dependent variable is the average target amount for successful projects in that location-week. Figure 7 shows that, for projects that successfully raise funds (i.e., raise at least the target amount), the target amount is indeed higher during breaks. We interpret this to be consistent with a relatively high value of contiguous time in improving project outcomes, β.

In order to ensure that the difference in Figure 7 is not driven by an increased likelihood of failure during breaks, we check that projects are no more likely to fail during breaks. Figure 8 shows that the probability of a project succeeding is approximately 10% higher during break weeks than work weeks. Therefore, Figure 7 and Figure 8 combined are consistent with a relatively high β underlying Prediction 3: Projects posted during breaks are at least as high value as projects posted during work weeks.

To further explore the mechanism driving value in the model, in Column (5) of Table 4 we analyze the difference in value for projects posted during breaks between Design and Technology projects versus projects in other categories before versus after the policy change. In particular, Prediction 3 suggests that as complexity rises, the relative value of projects posted during breaks should rise. The dependent variable in column (5) is the share of projects with large target amounts (over $30,000) in Technology and Design relative to the share of such projects in other categories. In other words, the dependent variable measures whether Technology and Design projects tend to have bigger goals. Prior to the policy change, there is no difference in goal size. After the policy change, the share of large goal projects in Technology and Design is significantly larger than for other categories. If we interpret goal size as a measure of value, then the increase in complexity due to the policy change in Technology and Design led to an increase in the value of such projects.

5.3.3 Imperfect Measurement for Predictions 2 and 3

Our analyses for Predictions 2 and 3 use proxy measures for project complexity and value. Three of these proxy measures are positively correlated with each other (team size, wait time, and goal size). For example, projects that seek to raise more money tend to have larger teams and longer wait times. In this way, our data do not allow us to separate the effect of coordination costs, ex-post project quality, and idea complexity. This means that we are unable to identify which one of these dimension is the most important in defining the comparative advantage of contiguous time during break weeks versus spare time during work weeks.

We assess the degree to which this affects our ability to interpret our data in light of our model in Figure 9. In particular, Figure 9 looks at the share of projects posted during breaks by team, wait time, and target amount. It shows that, even conditional on wait time and target amount, the share during breaks for projects with teams is higher than without teams. Similarly, conditional on goal and team, the share during breaks of above median target amount is higher than below median; and conditional on teams and time to delivery, the share during breaks is generally higher above median goal (though the differences are not significant for above median wait).

We interpret this to suggest that while each particular measure is an imperfect proxy for complexity and/or value, together the results are consistent with projects posted during break weeks being qualitatively different from projects posted during work weeks, even if the measures are individually imperfect. The break does more than generating marginal projects because of low opportunity cost time. Consistent with a high value of β in our model, more valuable and complex projects are posted during break weeks.

6 Conclusion

We explore if and how the availability of slack time influences the level and type of creative output. Our model generates three predictions: (1) More projects will advance to the fundraising stage during slack time, (2) If slack time helps focus or coordination, then more complex projects will advance during slack time, and (3) If the benefit of slack time for complex projects is large

enough, then projects that advance during slack time are more valuable. We empirically test these predictions by combining data on the location and timing of projects posted on Kickstarter with data on the timing of school breaks in locations with top US colleges. We find support for all three predictions.

As with any project, our analysis has a number of limitations. First, with respect to the generalizability of our empirical findings, we focus on the effect of a particular kind of slack time (school breaks) on a particular kind of creative endeavor (entrepreneurial and artistic projects posted on Kickstarter). While our model is more general, we recognize that, empirically, moving to other types of slack time and other types of creative endeavors may generate different results. Perhaps most obviously, if the benefit of slack time relates to complexity of coordinating across a team, then slack time that does not assign all team members the same break will not be helpful. Second, we observe the timing of posting on Kickstarter. We assume that the timing of posting is correlated with the timing of other activities related to the process of financing and developing an idea into a product. An alternative interpretation is that our empirical results are informative about the specific and idiosyncratic tasks related to posting on Kickstarter. The results are nonetheless consistent with our model in terms of its predictions on slack time, project quantity, and project complexity. Given this support for our model, our conclusions on the implications of slack time for innovation are driven by the model itself rather than by the specialized empirical setting of project posting on Kickstarter. Third, we cannot identify whether particular projects were started by students, professors, or other members of the local community because such information is often not provided. Thus, our results are strongly suggestive of slack time but we cannot identify projects as having been posted because specific individuals were on break. Fourth, our measures of complexity and quality are imperfect and we therefore emphasize the basket of results together in order to support our interpretation. Finally, as noted in the introduction, our measure of innovation reflects a single step in the multi-step innovation process. We most likely measure variation in the cost of preparing materials and advancing a prototype required for posting a project. In this way, one interpretation of our results is that they are most informative about complexity associated with the mundane, non-creative tasks associated with pitching an innovation and developing a working

prototype.

Notwithstanding these limitations, our results contribute to our understanding of how slack time affects creative output. They suggest that slack time can lead to an increase in creative projects, particularly relatively complex, high quality projects. As corporations place increasing emphasis on innovation, it seems not unreasonable that managers increasingly adopt the practices of universities and companies like Google and 3M, providing their employees slack time in order to advance the development of novel ideas.

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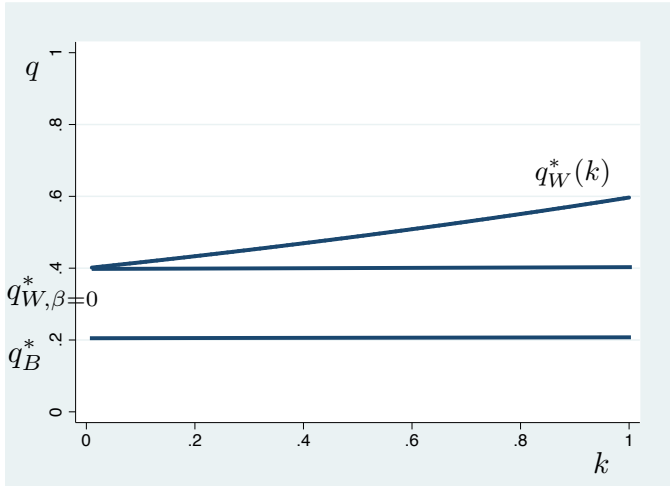
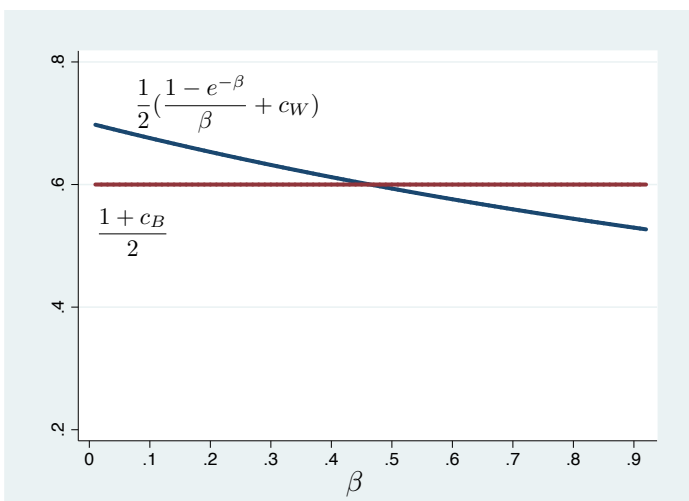
7 Figures and Tables

Figure 1: Thresholds for developing an idea (numerical example)



Notes: An idea is characterized by two parameters: ex-ante quality q and complexity k. This figure illustrates the thresholds in q above which an idea is developed using a numerical example ($c_B = 0.2$ and $c_W = 0.4$). q_B^* is for break weeks, $q_{W,\beta=0}^*$ is for work weeks when $\beta = 0$, and $q_W^*(k)$ is for work weeks when $\beta > 0$ ($\beta = 0.4$ in this particular example).

Figure 2: Expected overall value of projects (numerical example)



Notes: The figure illustrates the expected overall value of projects that are developed during the break (the horizontal line) versus during work periods (the downward-sloping line), both as a function of β. Similar to Figure 1, $c_B = 0.2$ and $c_W = 0.4$.

Table 1: Descriptives

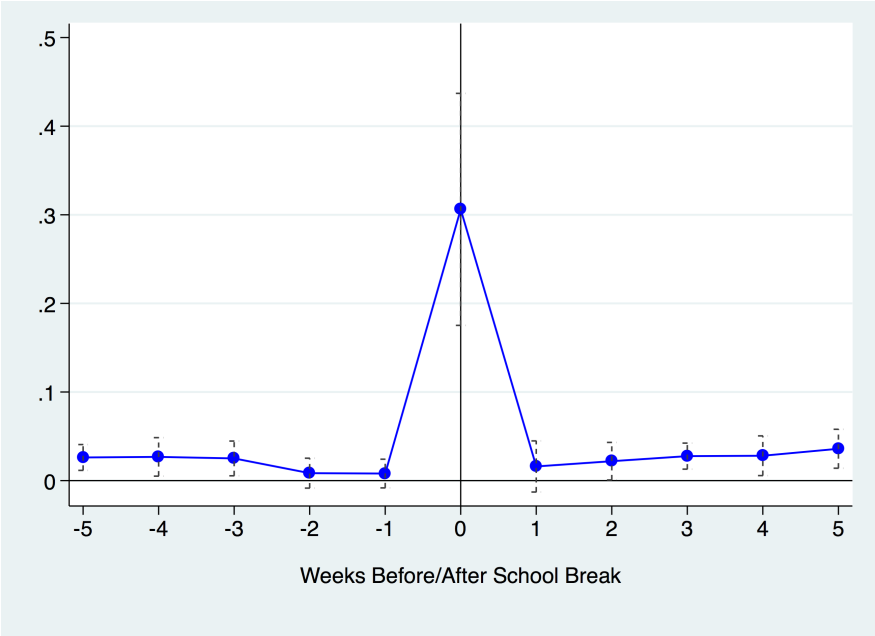
	Observations	Mean	Sd	Min	Max
Total Projects	3,178,665	.0520376	.7614194	0	114
Total Successful Projects	3,178,665	.0229052	.3980139	0	45
Total Failed Projects	3,178,665	.0291324	.4252265	0	79
Total Funding	3,178,665	444.6867	23,633.61	0	21.8M
Total Successful Funding	3,178,665	393.865	23,149.05	0	21.8M
Total Failed Funding	3,178,665	50.8217	1,784.375	0	623,041
All Breaks	3,178,665	.0348366	.1833659	0	1
Summer Break	3,178,665	.0206879	.1423374	0	1
Winter Break	3,178,665	.0075164	.0863705	0	1
Thanksgiving	3,178,665	.0000431	.0065649	0	1
Reading Week	3,178,665	.0030714	.0553352	0	1
Spring Break	3,178,665	.0035178	.0592069	0	1
Snow Day	3,178,665	.0011568	.0339917	0	1
Target Goal (Succ. Projects)	72,808	8,658.614	27,386.86	0	2,000,000
Target Goal (Failed Projects)	92,602	52,656.51	1,115,499	1	100,000,000
Wait Time for First Reward	149,299	85.06656	112.9642	0	2,155
Wait Time for Last Reward	149,299	171.3231	177.6822	0	2,156
Number of Team Members	165,410	2.795708	3.833561	1	228

Table 2: College Breaks and Kickstarter Funding

VARIABLES	(1) Projects	(2) Funding	(3) Log Funding
All School Breaks	0.0303***	57.1130	0.0562***
	(0.0085)	(264.0390)	(0.0108)
City Fixed Effects	YES	YES	YES
Week Fixed Effects	YES	YES	YES
Observations	3,178,665	3,178,665	3,178,665
R-squared	0.008	0.000	0.012
Number of Cities	10,091	10,091	10,091

Robust standard errors clustered at the city level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 3: The Number of Projects per Week is Higher During Breaks



Notes: Estimated Coefficient for Weeks Before and After the School Breaks. Dependent Variable is the Number of Projects Created in the Focal City-Week. Regression Includes Week Fixed Effects, City Fixed Effects, and City-Week Trends. Error Bars Represent 95% Confidence Intervals Based on Robust Standard Errors Clustered at the City Level.

Table 3: Evidence for a Causal Interpretation

VARIABLES	(1) Art	(2) Tech	(3) Funding Days 8-14	(4) Log Funding Days 8-14	(5) All Projects	(6) All Projects
All School Breaks	0.0020	0.0003	96.3529	0.0256	0.0495***	
	(0.0013)	(0.0004)	(88.8682)	(0.0162)	(0.0121)	
Break at Top Engineering School	-0.0007	0.0024**				
	(0.0032)	(0.0011)				
Break at Top Art, Design,	0.0053*	0.0003				
Film, Theatre School	(0.0028)	(0.0009)				
Snow Closing					0.0403**	1.2407***
					(0.0178)	(0.4758)
City Fixed Effects	YES	YES	YES	YES	YES	YES
Week Fixed Effects	YES	YES	YES	YES	YES	N/A
Year Fixed Effects	NO	NO	NO	NO	NO	YES
Observations	1,604,469	1,604,469	1,321,921	1,321,921	2,966,754	50,455
R-squared	0.001	0.000	0.000	0.002	0.008	0.013
Number of Cities	10,091	10,091	10,091	10,091	10,091	10,091

Robust standard errors clustered at the city level in parentheses. Columns 1 and 2 use data on Art-intensive versus Tech-intensive projects (available May 2012 to April 2015). Columns 3 and 4 use data on weekly investments (available from October 2012 to April 2015). Column 5 uses data on snow closing (available until December 2014).
The unit of analysis for Columns 6 is the city-year level. *** p<0.01, ** p<0.05, * p<0.1

Figure 4: Average Number of Team Members

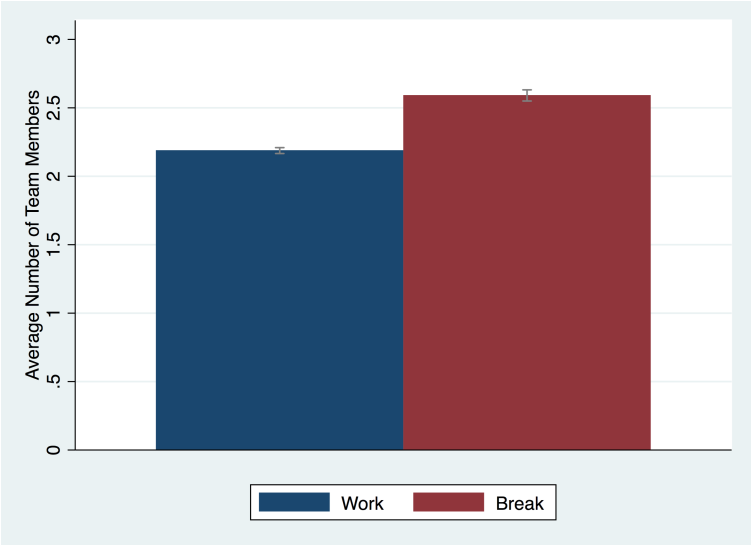
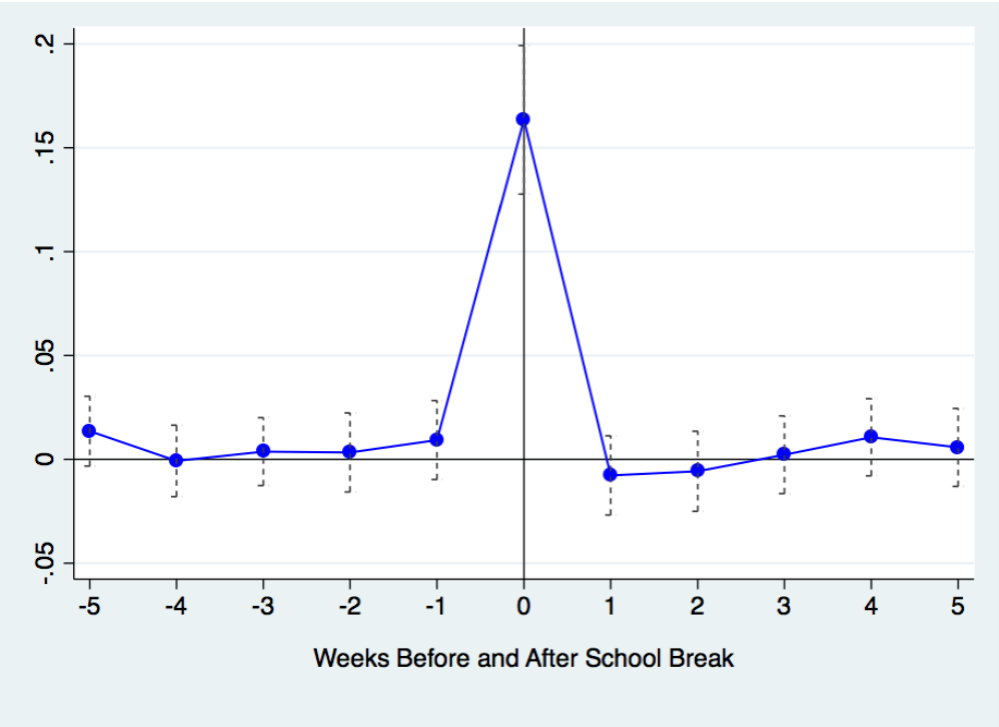


Figure 5: Average Number of Team Members is Higher During Breaks.



Notes: Estimated Coefficient for Weeks Before and After the School Breaks. Dependent Variable is the Average Number of Team Members. Regression Includes Week Fixed Effects, City Fixed Effects, and City-Week Trends. Error Bars Represent 95% Confidence Intervals Based on Robust Standard Errors Clustered at the City Level.

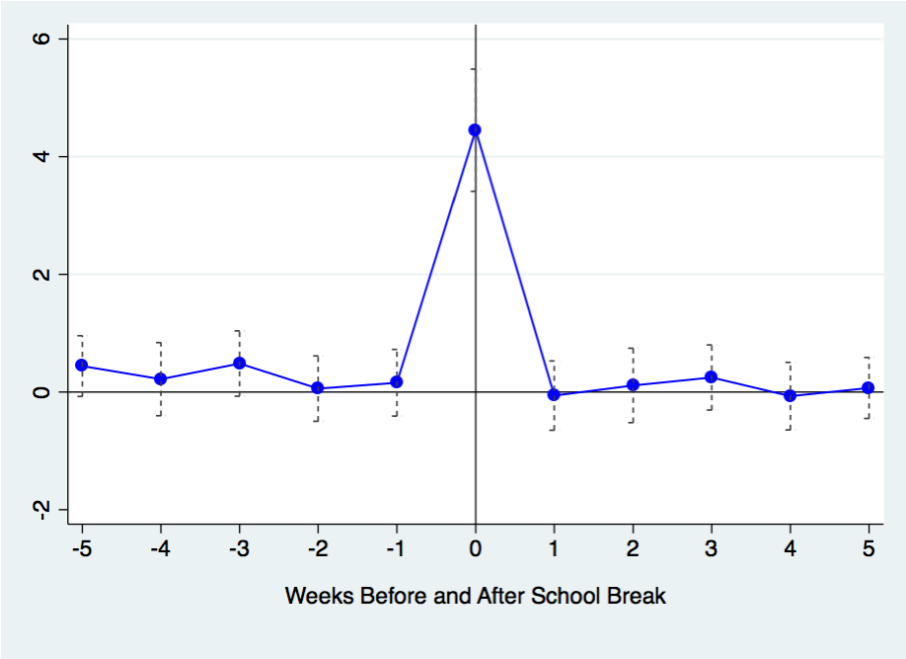
Table 4: Share of Projects and Funding in Design and Technology Before and After the Change

VARIABLES	(1) Share of Projects	(2) Share of Projects	(3) Share of Funding	(4) Share of Funding	(5) Share of Large Target †
All School Breaks		0.0017***		0.0034***	0.0062**
* After the Change		(0.0006)		(0.0008)	(0.0031)
All Breaks	0.0001	-0.0005	0.0005	-0.0009*	-0.0010
	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0008)
City Fixed Effects	YES	YES	YES	YES	YES
Week Fixed Effects	YES	YES	YES	YES	YES
Observations	3,178,665	3,178,665	3,178,665	3,178,665	3,178,665
R-squared	0.005	0.005	0.004	0.004	0.001
Number of Citites	10,091	10,091	10,091	10,091	10,091

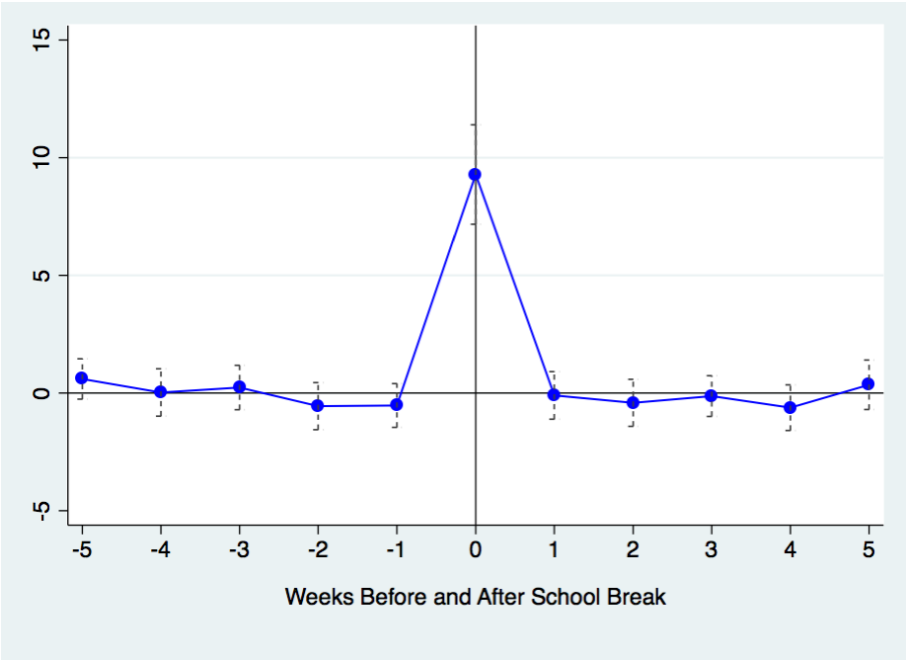
Robust standard errors clustered at the city level in parentheses. † is defined as share of large projects ($30K or larger) in Technology and Design over share of large projects in other categories. *** p<0.01, ** p<0.05, * p<0.1.

Figure 6: Average Wait Time is Higher During Breaks

(a) Average Wait Time for First Reward

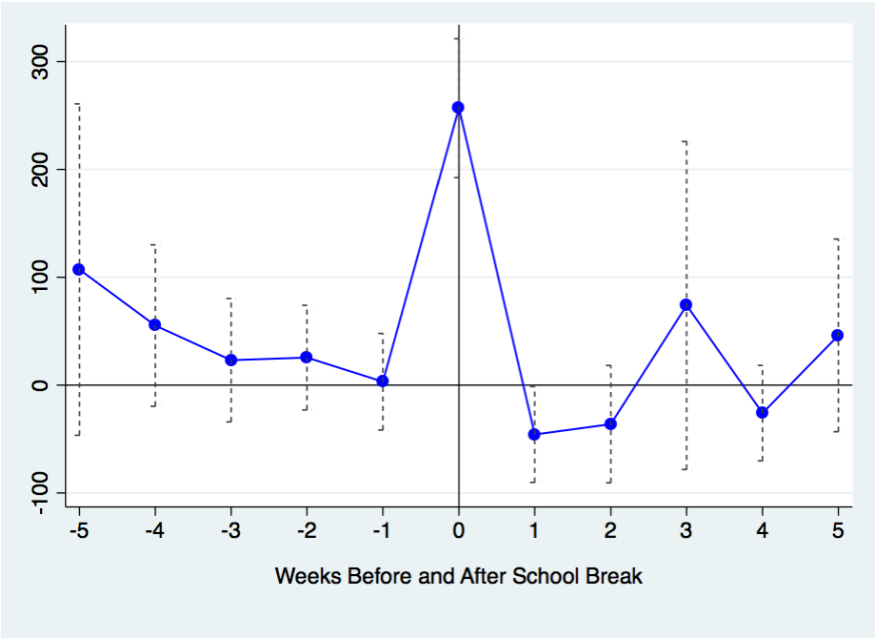


(b) Average Wait Time for Last Reward



Notes: Estimated Coefficient for Weeks Before and After the School Breaks. Dependent Variable is the Average Number of Days Backers Have to Wait for Reward. Regression Includes Week Fixed Effects, City Fixed Effects, and City-Week Trends. Error Bars Represent 95% Confidence Intervals Based on Robust Standard Errors Clustered at the City Level.

Figure 7: Average Target Amount For Successful Projects is Higher During Breaks



Notes: Estimated Coefficient for Weeks Before and After the School Breaks. Dependent Variable is the Average Target Amount For Successful Projects Created in the Focal City-Week. Regression Includes Week Fixed Effects, City Fixed Effects, and City-Week Trends. Error Bars Represent 95% Confidence Intervals Based on Robust Standard Errors Clustered at the City Level.

Figure 8: Probability of Success

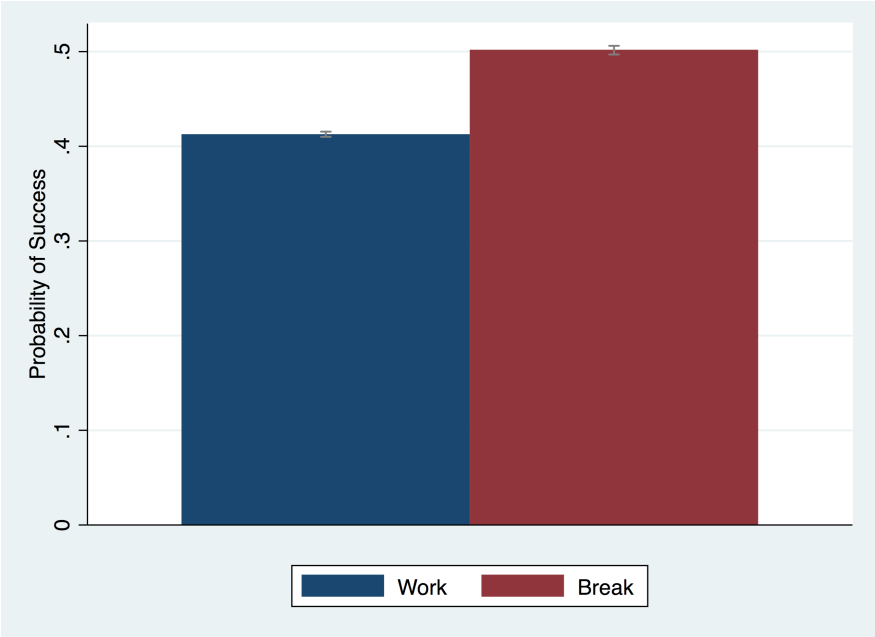


Figure 9: Share of Projects Posted During Breaks By Project Characteristics