

Small Victories: Creating Intrinsic Motivation in Task Completion and Debt Repayment*

Alexander L. Brown
Department of Economics
Texas A&M University
College Station, TX 77843
abrown@econmail.tamu.edu

Joanna N. Lahey
The Bush School
Texas A&M University
College Station, TX 77843
and NBER
jlahey@nber.org

Abstract: Tasks such as the elimination of all debts when faced with the immediate option to spend can be unpleasant but not conceptually difficult. Dividing these tasks into smaller parts and completing the parts from smallest size to largest can help individuals realize quick motivational gains that increase their likelihood of completing the task. This paper more broadly defines this idea as “small victories” and discusses, models, and empirically examines two related behavioral theories that might explain it. A laboratory experiment tests this prediction and provides data for model calibration. Consistent with the idea of small victories, when a task is broken down into parts of unequal size, subjects perform faster when the parts are arranged in ascending order (i.e., from smallest to largest) rather than descending order (i.e., from largest to smallest). Our calibrated model is consistent with the directional predictions of each theory. However, when subjects are given the choice over orderings, subjects choose the ascending ordering least often. The final section discusses the efficacy of this method in stylized debt repayment scenarios.

Keywords: behavioral economics, experimental economics, motivation, consumption/savings

* This paper benefitted from helpful comments at the 2012 North American Economic Science Association Meetings, the 2013 National Bureau of Economic Research Summer Institute, the first annual Texas Experimental Association Symposium, and the Bush School Methods Brown Bag. We also received helpful comments from Gary Charness, Martin Dufwenberg, Catherine Eckel, Pablo Brañas-Garza, John Kagel, and Brandon Schmeichel. We especially thank José Gabriel Castillo, Gregory Cohen, Luke Franz, Matthew Liu, Laura Lombardo, Daniel Stephenson, Britnee Warmerdam, J. Forrest Williams, and Xiaoyuan Wang for help running, designing and transcribing data from experiments. We thank the International Foundation for Research in Experimental Economics for financial support for subject payments under their Small Grants Program.

Many large tasks can be broken into a set of smaller, distinct, subtasks. Completing all subtasks is equivalent to completion of the initial task. Examples include incremental subgoals for health or physical training outcomes, dividing projects at work, home, or school into separate parts, or setting smaller financial goals in savings or debt repayment. While previous work demonstrates the value of breaking up a larger goal into smaller subgoals (e.g. Bandura and Schunk, 1981; Bandura and Simon 1977; Kettle et al. 2014; Latham and Seijts 1999; Morgan 1985; Stock and Cervone 1990), other work suggests motivation to complete these smaller subgoals may distract from or crowd-out motivation to complete the ultimate goal (cf. Amir and Ariely 2008; Fishbach and Dhar 2005; Fishbach, Dhar and Zhang 2006; Heath, Larrick and Wu, 1999). Less work examines the question of the optimal division and ordering of these smaller subgoals. To this end, we provide a unifying, formalized model of task completion that incorporates the very models and psychological tendencies that underlie this debate.

Our motivating example for this type of analysis is debt reduction. The use of debt is one part of a consumer's lifetime consumption/savings decision, a decision that empirical evidence suggests is not made optimally (see Bricker et al. 2012). Unlike most other parts of that decisions which require knowledge of the basic principles of dynamic optimization and financial markets ("financial literacy" see Lusardi and Mitchell 2014), the underlying concept behind getting out of debt is simple—spend less than you earn and apply the excess towards debt. In the area of financial decision-making, self-control issues are significant (e.g. Raab et al. 2011; Rick et al. 2008) and can plague even the most financially literate (Brown, Chua and Camerer, 2009).

The standard economic approach, neither equipped nor designed to handle these self-control issues, advocates paying off debts in order from highest to lowest interest rates because mechanically this method results in the least amount of money paid to interest. Recent self-help

books for debt-reduction have advocated a new, economically sub-optimal strategy, called the “debt snowball.” This principle suggests there may be an additional motivational benefit for a person paying off his or her smallest debt first, and then paying the rest of his or her debts from smallest to largest. As radio personality and author Dave Ramsey (1998; 2009) suggests,

“The reason we list [debts from] smallest to largest is to have some quick wins...When you start the Debt Snowball and in the first few days pay off a couple of little debts, trust me, it lights your fire...When you pay off a nagging \$52 medical bill or that \$122 cell-phone bill from eight months ago, your life is not changed that much mathematically yet. You have however, begun a process that works, and you have seen it work, and you will keep doing it because you will be fired up about the fact that it works.” (Ramsey 1998, p. 114-117)

Ramsey’s quote suggests *after* completing a small step, task, or “subgoal” one increases motivation towards the ultimate goal. The idea is closely aligned with the concept of “self-efficacy” in social cognitive theory (Bandura 1977; 1986). That is, successful past subgoal completion provides an emotional boost that pushes one through the next subgoal.¹

Empirical research appears to support this debt-repayment method. Gal and McShane (2012) find that people who use the debt snowball are more likely to eliminate their debt balance controlling for debt size in comparison to other methods. The evidence from stylized laboratory experiments is mixed; Kettle et al. (2014) find that subjects who pay down debts one-at-a time are more committed to debt repayment than those who try to pay all simultaneously. When subjects are given a purely financial decision making task involving debt repayment, Amar et al. (2011) find that when given a choice, individuals reject this economically optimal method in

¹ Social cognitive theory is not the exclusive explanation for phenomena like these. More recent intrapersonal game-theoretic models and modern re-interpretations of the goal-gradient hypothesis also suggest successful past-performance may spur future performance. Benabou and Tirole (2004) model an intrapersonal game where agents with imperfect memory are more likely to persevere after past success, because that past success signals they are a high-type, a type that would make their perseverance more beneficial. Kivetz, Urminsky, and Zheng (2006) and Nunes and Dreze (2006) both demonstrate any perceived advancement toward a goal, even artificial, increases performance and consider the result to be a part of an interpretation of goal-gradient theory that differs from the interpretation we discuss below. However, these alternate explanations are noticeably less in the spirit of the Ramsey quote.

favor of the economically sub-optimal debt-snowball approach, paying off their small debts first regardless of interest rate and then progressing to larger debts, even though doing so means that they pay more money in interest. They reason,

“To the extent that becoming debt free is perceived as a difficult superordinate goal, consumers may adopt subgoals focused on paying off individual loans. The danger in such an approach is that focusing on and achieving subgoals can actually diminish the motivation to pursue superordinate goals...consumers may be more motivated to achieve goals that are proximal (e.g., paying off debts with small balances) than goals that are distal (e.g., becoming debt free).” (Amar et al., 2011, p. S39)

The authors explain the mechanics of the debt-snowball with a different motivational theory, the “goal-gradient hypothesis” (or alternatively, “discrepancy theory”). The theory posits that the closer one gets to completing a goal, the more motivated one is to complete it (Heilizer 1977; Hull 1932). A modern reinterpretation of the theory hypothesizes the goal-gradient creates motivation to complete subgoals in the same way. As Amir and Ariely (2008) explain,

“A goal...is the focal point of directed activity...the goal gradient becomes steeper as one approaches goal attainment...this effect is true for each subgoal in a task...approaching a subgoal may motivate activity toward the subgoal.” (Amir and Ariely, 2008, p. 1159)

Thus, both the original debt-snowball statement and its critique suggest motivational forces are in place and directed at the subgoal. The key difference in the explanations, however are that the original statement suggests increased motivation occurs *after* the subgoal is completed (henceforth, “post-subgoal” motivation), while the critique suggests the subgoal create increasing motivation *until* its completion (henceforth, “pre-subgoal” motivation) and then reduced motivation thereafter.

Our paper attempts to reconcile these two opposing views and associated psychological theories with a formalized model of motivation and task completion. The model includes terms to allow both *post-* and *pre-* subgoal motivation as described in the debt-snowball approach and

its critique, respectively. Under a few general assumptions, the model allows us to make general predictions about how dividing and ordering a superordinate goal into small subgoals will affect superordinate goal completion. The debt-snowball idea would suggest people can motivate themselves to greater task completion by first completing an easier related task. That is, a larger project is not only broken up into smaller tasks, but the tasks are ordered to become progressively larger or more difficult. We term this general approach “small victories.” Our first proposition validates the small victories approach: if a task is already divided into predetermined subtasks, as long as post-subgoal motivation exists—as in social-cognitive theory—optimal performance is achieved by completing subtasks in ascending order.

If we relax the assumption of predetermined subtasks and allow any configuration of subtasks, a configuration of all subtasks of equal size could be optimal, provided pre-subgoal motivation, as in modern goal-gradient theories, is strong enough. Thus, of the two motivational effects, only post-subgoal motivation is necessary for the small victories approach to work, but both theories have implications on what type of order of subtasks might be optimal for task completion.

To test these predictions, and ultimately to affirm the validity of the small-victories approach, we develop a laboratory experiment that allows us to isolate the underlying motivational mechanics of small victories. To simulate this more general process, we choose a task that is unpleasant but not conceptually difficult. In 30 minutes, subjects attempt to retype 150 ten-character strings in a Microsoft Excel workbook. The strings are divided over 5 columns where the length of the columns is ascending, descending or even throughout as subjects progress. The completion of each column is framed as a distinct event for each subject. Subjects are given continual feedback of how many cells are left in their current column.

Unlike previous studies that focus explicitly on debt repayment scenarios, we abstract away from debt repayment in order to study the underlying psychological theories and to make sure that our subjects are uncontaminated with popular suggestions on how to repay debt. By providing discrete tasks (cells) inside a subgoal (columns), we maintain the general structure of the n payments until completion of a debt. The continual feedback directed at the completion of a column rather than the entire tasks focuses subjects toward the completion of a column, making the subgoal, and perhaps the accompanying motivational factors, more salient. However, an unintended effect of this feedback is that this discrete feedback may create as “artificial landmarks” within a subgoal that may be adopted as “sub-subgoals.” Since there is no theory of sub-subgoals, we must exercise caution about the general conclusions we make about motivational theories until a similar experiment is adopted with either entirely no feedback within a subgoal or completely continuous feedback within a subgoal.

That caveat aside, our results show that subjects complete a tedious task faster when it is broken up into parts in order of ascending length compared to descending or equal lengths. Further analysis—which shows subjects speed up as they approach the end of columns and slow down at the beginning of columns—provides support for pre-subgoal motivation and the application of goal-gradient theories to subgoals. However, the fact that ascending length orderings are completed faster than orderings of equal lengths, something that our experimental set-up allows us to test, demonstrates that post-subgoal, social-cognitive factors dominate pre-subgoal, goal-gradient factors in our environment. Our model calibration further confirms these general results, providing evidence of both pre- and post- subgoal factors, and we provide an estimate to what extent post-subgoal factors dominate pre-subgoal factors.

Interestingly, in a second study we find when subjects are given the opportunity to

choose among all three orders they choose the ascending ordering, the one that provides the most motivational benefit, *least* often. Additionally, regression results suggest there is subject heterogeneity in the benefits of the small victories approach. Those with higher self-control, better critical reasoning skills, and higher risk aversion, as measured by survey results, benefit more from having chosen ascending. We argue a plausible extension of this result suggests the people least in need of this intervention are the ones most likely to benefit from it.

Taken at face value, our results suggest there is some benefit in the form of intrinsic motivation in using the small victories approach in field scenarios. While it will take substantial investigation to determine the exact magnitude of this benefit in field situations, we show in our final section that it will only be useful to borrowers in specific cases of debt reduction where interest rates between loans do not differ greatly. In the event of large differences in interest rates on loans, it will be best for consumers to pay off debts from highest interest rate to lowest, despite the additional motivational benefit from the small-victories approach.

Theory

We develop a formalized, theoretical model of task-competition. Our aim is to demonstrate how psychological theories may create a motivational boost like small victories. Our theoretical propositions will provide testable predictions about how these theories will work and whether they may be responsible for the (potential) efficacy of small victories. We illustrate the intuition of the formal theory in the framework of a debt-repayment problem for ease of intuition. It is important to note that even though this discussion is framed in terms of debt repayment, the theory is relevant to any type of task completion where the main task can be perceived as having separate discrete subgoals. The full formalization is available in the appendix.

We view the main task as X , the removal of all debt. X is a set consisting of individual payments of x . The individual payments are grouped and ordered by α , a partition of X that divides the payments into individual debts and orders the debts in the order in which they will be paid. For consistency with the goal-setting literature: it is important to note that x is the smallest individual element in our discrete model. The partition α divides our ultimate goal X into a number of subgoals. The term x is not a goal and would not exist in a continuous model.

The function $\tau_i(x, \alpha)$ determines the amount of time that it takes an individual, i , to complete an individual debt payment, x . This function is a linear combination of two functions: $h(\cdot)$, a function of how many payments are left in the current individual debt, and $v(\cdot)$ how many individual debts have been completed. These components, $h(\cdot)$ and $v(\cdot)$, effectively represent the pre-subgoal motivation of the goal-gradient and post-subgoal motivation of social cognitive theories, respectively. Recall, goal-gradient theories suggest individuals speed up as they approach the completion of a goal; this can be represented as h increasing. Similarly, social-cognitive theories suggest that individuals increase performance after past success; this can be represented as v decreasing.

Variation in performance in the time to make a payment depends on the grouping and ordering of the individual debts. The partition $\alpha=(\alpha_1, \dots, \alpha_k, \dots, \alpha_m)$ is made up of m ordered sets, each set can be thought of representing an individual debt. Each set α_k ($k=1, \dots, m$) is composed of $|\alpha_k|$ debt payments where $l=1, \dots, |\alpha_k|$ represents the l th payment in debt k . Then individual i 's performance in making payment x given debt order α is

$$\tau_i(x, \alpha) = \tau_i(\alpha_{kl}) = \mu_i + h(|\alpha_k| - l) + v(k) + \gamma_w + \varepsilon_{i\alpha_k}, \quad (1)$$

where μ_i represents individual i 's baseline performance, $|\alpha_k| - l$ represents the number of payments to the end of the current debt, k , and $k - l$ is the number of previous debts successfully paid. The term γ_w represents any performance change due to payment x being the w th payment independent of subgoal partition.² The term and $\varepsilon_{i\alpha_{kl}}$ represents any idiosyncratic error associated with person i completing element x . By definition and assumption, μ_i , γ_w , and $\varepsilon_{i\alpha_{kl}}$ are not dependent on subgoal partition. Thus we may write the total impact due to these effects as $C_i = \sum_{x \in X} \mu_i + \gamma_w + \varepsilon_{i\alpha_{kl}}$.

The total time it takes to remove all debts under α , $T_i(\alpha)$, is the sum of all $\tau_i(x, \alpha)$,

$$T_i(\alpha) = \sum_{x \in X} \tau_i(x, \alpha) = C_i + \sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} h(|\alpha_k| - l) + v(k). \quad (2)$$

Note that the model presented here is based on productivity, not utility. Equations (1) and (2) represent the time it takes an individual to complete a task—something that could be modeled as the result of utility maximization process—rather than the utility derived from completing a task.³

For our first proposition, we will incorporate post-subgoal factors from social-cognitive theory into our model. We will do this by assuming that v , the post-subgoal motivational

² The term γ_w affords our model great freedom. Whether individuals speed up as they progress along the task (as in a traditional goal-gradient model), slow down due to fatigue, or have some other relationship as they progress (e.g., Bonezzi, Brendl, and De Angelis, 2011 find that aggregate performance is U-shaped), all of these things will not affect our model's main result, provided they occur independent of the subgoal partition.

³ Such models represent underlying preferences and psychological processes which determine behavioral outcomes. Because the literature that inspires our model primarily focuses on behavioral outcomes (e.g., task persistence, task completion, speed), our model only focuses on behavioral outcomes leaving out the underlying psychological processes that generate those outcomes.

One could use a simple quadratic, $u(\tau_i) = -0.5\tau_i^2 + [\mu_i + h(|\alpha_k| - l) + v(k) + \varepsilon_{i\alpha_{kl}}] \tau_i + c$ (where c is any constant) to generate equation (1) as its maximizing condition. Setting up equation (1) as the solution to a dynamic maximization problem over the entire task T , is difficult and likely would require additional assumptions to be made on the functional form of equation (1). Because of this difficulty, and the fact it is difficult to explain the intuition in the functional forms of these possible utility functions, we only focus on functions that represent task performance.

function, is non-increasing. In other words, after an individual debt is paid off, the debtor is motivated to pay off future individual debts faster or at least as fast as previous debts. If this assumption is true, then the debtor would want to get a quick boost immediately in order to benefit from the increased productivity. If one can only re-order debts, but is unable to change the structure of any debts (i.e., the number of payments inside a debt), then ordering debt from smallest to largest, something we are terming an ascending ordering, would result in the fastest debt repayment, while ordering debts from largest to smallest would be the slowest.

To formalize this idea we define $A(X)$ as the set of all subgoal partitions that could be formed from X . We define a class of subgoal partitions as a subset of $A(X)$ where all terms differ by only the re-ordering of subgoal. Each possible re-ordering is included in the set. Using this terminology, Proposition 1 demonstrates the superiority of an ascending ordering in this case, the central tenant of the small victories approach.

Proposition 1. *For any i , for a given class of subgoal partitions, $\beta \subseteq A(X)$. Define an ascending ordering, α' where*

$$|\alpha'_1| \leq \dots \leq |\alpha'_k| \leq \dots \leq |\alpha'_m|,$$

and a descending ordering where

$$|\alpha''_1| \geq \dots \geq |\alpha''_k| \geq \dots \geq |\alpha''_m|.$$

Then for any $\alpha \in \beta$,

$$T_i(\alpha') \leq T_i(\alpha) \leq T_i(\alpha'').$$

If v is non-constant and $\alpha' \neq \alpha''$, $T_i(\alpha') < T_i(\alpha'')$.

Proposition 1 shows that all that is required for the small victories approach to be effective in our framework is that the assumption of increasing post-subgoal motivation found in social-cognitive theory holds. It requires no assumptions about pre-subgoal motivation;⁴

⁴ This point should be stressed. Whether individuals speed up as they progress within the subgoal (as in a modern interpretation of a goal-gradient model), slow down due to fatigue, or have some other relationship as they progress

conditions on function h are irrelevant in the proof of Proposition 1 (available in the appendix). Thus, under the general assumptions of social-cognitive theory, the small victories approach works: arranging subtasks in ascending order leads to better performance.

Given that ascending orderings are optimal when the post-subgoal motivational assumptions of social-cognitive theories hold, a remaining question is what structures might be ideal for task completion under the pre-subgoal motivation of the competing goal-gradient theory. If pre-subgoal motivation holds and the effect of post-subgoal motivation is zero, then an even ordering, that is, a main task divided so that all subgoals are of the same length, will be ideal. In the context of debt-repayment this is equivalent to having our m debts have exactly the same number of payments.⁵ If we enact these pre-subgoal motivational assumptions,⁶ this ordering is optimal relative to any other possible ordering (Proposition 2) with the same number of debts.

Proposition 2. *Suppose v is constant. Then for any X , i , and m , if there exists an even ordering $\alpha' \in A(X)$ such that $|\alpha'_k| = c$ for all $1 \leq k \leq m$ then*

$$T_i(\alpha') \leq T_i(\alpha) \quad \forall \alpha \in A(X) \text{ where } |\alpha| = |\alpha'| = m.$$

Further, if all the subgoals in α are not of the same length and h is strictly increasing, $T_i(\alpha') < T_i(\alpha)$.

In other words, we assume pre-subgoal motivation exists and post-subgoal motivational factors have no impact. Here, what is important to debt-repayment productivity is how close you

(e.g., U-shaped performance within a subgoal), Proposition 1 will still hold. Ascending orderings are best and descending orderings are worst.

⁵ This type of ordering may be impossible to construct in an actual debt-repayment situation. One of the benefits of a laboratory setting is our ability to test the components of this theory.

⁶ That is we assume h is non-decreasing, meaning motivation increases or at least does not decrease the closer one gets to the end of a debt. We also hold v constant.

are to paying each individual debt—how close you are to the end of the task.⁷

Unlike Proposition 1, which places no restrictions on its competing theory, Proposition 2 requires the effects of the post-subgoal motivational factors of social-cognitive theory to be zero. This added assumption allows Proposition 2 to apply to a much greater domain.⁸ It is possible to make equivalent assumptions (i.e., make the pre-subgoal effects zero) and show an ascending ordering is optimal across a similar domain. The result is Proposition 3.

Proposition 3. *Suppose h is constant. Then for any X , i , and m , there exists a subgoal partition $\alpha' \in A(X)$, in ascending order, $|\alpha'_1| \leq \dots \leq |\alpha'_k| \leq \dots \leq |\alpha'_m|$, for all $1 \leq k \leq m$, such that*

$$T_i(\alpha') \leq T_i(\alpha) \quad \forall \alpha \in A(X) \text{ where } |\alpha| = |\alpha'| = m.$$

Further, if α is not ascending and v is strictly decreasing, $T_i(\alpha) < T_i(\alpha')$.

Propositions 2 and Proposition 3 are based on different assumptions. With Proposition 2, only pre-subgoal motivation exists, meaning completion of past subgoals does not matter, and only distance to the end of those subgoals matters. In such case the even ordering will feature better subject performance than either ascending or descending orderings. Alternatively, when only post-subgoal motivation exists, successful completion of past subgoals matters and distance to the end of subgoals does not matter. In such a case the ascending ordering will feature better subject performance than either even or descending orderings.

Both factors may be present in subject behavior; therefore we would like to have a way to talk about the relative strength of each factor. To this end, we develop the concept of “dominance.” For any two subtask partitions, we say the post-subgoal, social-cognitive, factors

⁷ This conclusion is more obvious using another task completion example. If instead of debt repayment, we think of port-a-potties at an amusement park, where the distance to the end is the only thing that matters, optimally all lines will be the same size. (Similarly you could think of sorting into “10 items or less” lines at the grocery store.)

⁸ Proposition 2 shows an even ordering with m subgoals is optimal over *any arrangement* of elements into m subgoals. Proposition 1 shows that an ascending ordering with m subgoals is optimal over *any arrangement* of those subgoals. The domain in Proposition 2 necessarily contains the domain of Proposition 1.

dominate the pre-subgoal, goal-gradient, factors if the total differences across the post-subgoal term are greater in magnitude than the total differences across the pre-subgoal term. (See Appendix for a formal definition of dominance.) Alternatively, we say the pre-subgoal factors *dominate* the post-subgoal factors if the previous relation is reversed. If both magnitudes are equal, then there is no dominance.

Proposition 4 shows that our definition will be useful in explaining results. Over a given three orderings, ascending, descending, and even, subject performance in the ascending ordering will be faster than even *if and only if* post-subgoal factors dominate pre-subgoal. Subject performance in the even ordering will be faster than ascending *if and only if* pre-subgoal factors dominate post-subgoal. If there is no dominance, the performance of subjects on ascending and even orders should be the same.

Proposition 4. *For a given Δ -set, $\{\alpha^a, \alpha^d, \alpha^e\}$ where all the subtasks in α^a are not of the same length, for any i ,*

1. $T_i(\alpha^a) < T_i(\alpha^e)$ *if and only if* post-subgoal factors dominate pre-subgoal factors.
2. $T_i(\alpha^a) > T_i(\alpha^e)$ *if and only if* pre-subgoal factors dominate post-subgoal factors.
3. $T_i(\alpha^a) = T_i(\alpha^e)$ *if and only if* there is no dominance between post-subgoal and pre-subgoal factors.

Our theoretical framework is agnostic on whether ascending or even orders will lead to optimal task performance—it depends entirely on the relative strength of the pre- and post-subgoal factors. However, it does have a clear result about the descending ordering in the Corollary to Proposition 4.

Corollary. *For a given Δ -set, and any i , $T_i(\alpha^d) \geq T_i(\alpha^a), T_i(\alpha^e)$. Provided all the subtasks of α^d are not of the same length, $T_i(\alpha^d) > T_i(\alpha^a)$ if v is non-constant; $T_i(\alpha^d) > T_i(\alpha^e)$ if either v is non-constant or h is strictly increasing.*

Proposition 1 already tells us that a descending ordering should be completed more slowly than the ascending ordering. The Corollary shows that provided *either* the v function is non-constant or the h function is strictly increasing (either pre- or post-subgoal factors exist under certain conditions), the even ordering should be completed faster than the descending ordering. To frame this in terms of debt repayment, completing one's debts in descending order leads to the least motivational gains.⁹ Our experiments will compare ascending, descending, and even-length orders to test these predictions. The Theoretical Predictions section will discuss this theory in the context of our experiment.

The Experiment

Design

In the experiment, subjects typed ten-character lines of text in a Microsoft Excel worksheet. Subjects would type a line of text in a cell and then click a button on their worksheet. If they typed the line correctly, they would move to the next cell; if they typed it incorrectly, nothing would happen until they typed the line of text correctly. The lines of text included upper and lower case letters, numbers and their shifts¹⁰ (e.g., !#) and had been randomly constructed before so that each subject encountered the same order and same lines of text in cells.

The experiment had two main parts: a practice session, and one large typing task. Subjects would either complete their tasks or reach the time limits.¹¹ The practice session had a 5-minute time limit, and the large typing task had a 30-minute time limit. The practice task was the same for all subjects. It consisted of each subject typing ten lines of text. It was designed to

⁹ Note that the existence of pre-subgoal factors make no prediction on whether ascending or descending should have greater performance. Any superiority of ascending compared to descending comes from post-subgoal factors.

¹⁰ To avoid confusion the characters “I,” “l,” and “|” were excluded. The sign “@”, which produces a hyperlink in Excel, was also excluded.

¹¹ After the typing tasks, subjects had a ten-minute break and then participated in various pilots of future typing tasks. Subjects were aware of this second 30-minute session at the beginning of their experiments. The results of the pilot sessions are not presented here and are not relevant to the data analysis or conclusions of this paper.

familiarize subjects with the experiment as well as to get an estimate of their general skill in these typing tasks.

The larger, 30-minute, tasks varied depending on the environment, but all tasks featured subjects encountering 150 lines to type divided into 5 columns. In the initial study (as opposed to the “choice” study described later), subjects were randomly assigned to three orders. In the “ascending ordering,” the columns increased in size. The columns had 10, 20, 30, 40, and 50 cells respectively. In the “descending order,” the columns decreased in size and had the reverse ordering of the ascending (50, 40, 30, 20, and 10). In the “even ordering” all columns had 30 cells. Figures 1(a-c) provide screenshots of the initial worksheet under each of the three orders.

Subjects completed their columns in order, left to right. Unless completing a column, every time a subject finished a cell he or she would move down to the next cell below the current cell. To frame column completion as a distinct event, the experimental interface would open a message box every time a subject completed a column. For all columns but the last column, the message said “You have completed X columns. Only 5-X to go!” Once subjects clicked ok on that message, they moved to the cell at the top of the next column to the right. When subjects finished the last column, a similar message informed them they had finished the task.

Subjects were paid \$10 if they could complete the task in under 30 minutes, plus an additional \$0.50 for every minute they finished early, rounded up to the nearest minute. Subjects that did not complete the task were paid \$10 minus \$0.05 for every cell they left uncompleted. Because this structure guarantees a minimum payment for subjects, there were no additional payments given to subjects (i.e., show up fees).

After examining the results of the initial study of subjects, one remaining question was how subjects might have chosen among the orders if given that choice. This question led to the

creation of a second, “choice” study. The study featured the same task and basic design as the first, except that before the experiments began, subjects were allowed to choose whether they would encounter the ascending, descending or even ordering. The experimenter showed pictures (nearly identical to those shown in Figure 1) of each ordering on a screen with randomized names (i.e., “a”, “b” and “c”) and subjects would click on any of three icons corresponding to those names. After the subjects clicked on the icon, they would have a five-minute practice session and a 30-minute typing task. Again, the second half of the experiments was used for piloting other effort tasks.

It is important to reiterate that these experiments were not designed to mimic any field scenarios, but rather to test the underlying psychological theories of motivation that might affect such scenarios. For instance, like debt repayment, these experiments involve tasks that are mildly unpleasant but not conceptually difficult. However, in order to focus on the most basic features of the “small victories” scenario, the experiment did not feature the full debt repayment scenario including interest rates, minimum payments, and so on.

Procedure

Both studies took place at the Economic Research Laboratory at Texas A&M University. Subjects were recruited from the econdollars.tamu.edu website that uses ORSEE software (Greiner 2004). Subject earnings averaged \$11.25 for the 35-minute session, with subjects in the initial study averaging \$10.95 and subjects in the choice study averaging \$11.63.¹²

Ninety-one subjects participated in the initial study between December 6, 2011 and March 7, 2012. Subjects completed a demographic survey (from Eckel and Grossman 2008), the Barratt Impulsivity Test (BIS 11) (Patton, Stanford, and Barratt 1995), the Zuckerman Sensation-

¹² Including the second pilot task, subject earnings averaged \$21.67 for 75 minutes, with initial study subjects averaging \$20.01 and choice study subjects averaging \$23.83.

Seeking Scale (SSS-V) (Zuckerman 1994) and a five-factor personality assessment (John, Naumann, and Soto, 2008).¹³

Seventy subjects participated in the choice study between January 30-31, 2013. Because the first set of surveys had little explanatory power and helpful suggestions brought other surveys to the attention of the authors of this paper, a second set of surveys was used in the choice study. Subjects completed a demographic survey and non-incentivized risk-preference choice to elicit risk attitudes (both from Eckel and Grossman 2008), financial literacy questions from the Health and Retirement Survey (Lusardi and Mitchell 2007b), the Tangney-Baumeister-Boone Scale (Tangney, Baumeister, and Boone. 2004), and the Cognitive Reflection Task (Frederick 2005).

Theoretical Predictions

Our theoretical framework shows that an ascending ordering is the ideal structure for task completion if only post-subgoal factors matter (Proposition 3), an even ordering is the ideal structure if only pre-subgoal factors matter (Proposition 2), and as long as post-subgoal factors exist an ascending ordering should do better than a descending ordering (Proposition 1).

Proposition 4 ties these three propositions together in an environment where both pre- and post-subgoal motivational factors may exist. It uses the term “dominance” to classify whether pre- or post-subgoal factors have greater influence on results. Its corollary also shows that the descending ordering should have the worst performance regardless of the relative strength of these factors. Because it is much like a cumulative proposition in this way, the predictions for this experimental environment can be found entirely in Proposition 4 and its corollary.

¹³ None of these three personality tests in the initial study were correlated with any subject performance measures (see Appendix, Table 3). We will not discuss these tests in relation to our results. In retrospect, it would have been preferable to replace these surveys with the surveys used in the choice study (see below).

Prediction 1a (Proposition 4). If post-subgoal factors dominate pre-subgoal factors across our orders, subjects in the ascending orders will finish faster than those in the even orders, and be more likely to complete their tasks in the time allowed. Formally,

$$t_A < t_E, \quad p_A > p_E.$$

where t is the time to completion and p is the probability of completion.

Prediction 1b (Proposition 4). If instead pre-subgoal factors dominate post-subgoal factors, subjects in the even orders should finish faster than those in the ascending orders, and be more likely to complete their tasks in the time allowed. Formally,

$$t_E < t_A, \quad p_E > p_A.$$

Prediction 2 (Corollary to Proposition 4). Regardless of dominance, subjects in both ascending and even orders should finish faster than those in descending orders, and be more likely to complete their tasks in the time allowed. Formally,

$$t_A, t_E < t_D, \quad p_A, p_E > p_D.$$

Combining these predictions we have one of two possible predicted orderings,

- 1a.** $t_A < t_E < t_D$ if post-subgoal factors dominate,
- 1b.** $t_E < t_A < t_D$ if pre-subgoal factors dominate.

Because small victories (or in relation to debt, the debt snowball, Ramsey 1998; 2009) recommends ordering tasks in ascending order to create maximum motivational gains, the advice is most consistent with environments where post-subgoal factors (and corresponding social-cognitive theories) dominate. Thus the greatest validation of small victories (and social-cognitive theory) would be if Prediction 1a held. If, instead, even orderings are faster than both ascending and descending, then pre-subgoal factors dominate post-subgoal factors (and corresponding goal-gradient theories). However, in most cases of debt repayment arranging one's debt in an even

ordering is not possible, while paying debt in ascending and descending orders is possible. So as long as ascending orders are faster than descending orders we would find validation of the concepts behind the small victories approach (and Proposition 1).

Our underlying psychological theories also make predictions about subject performance in specific columns throughout the experiment. If our assumptions of post-subgoal motivation based off social-cognitive theories are valid, we should see subjects speed up as they complete more columns. If our assumptions about pre-subgoal motivation in goal-gradient theories are valid, subjects should perform faster as they reach the end of each column.

Results

Time to completion and probability of completion (Predictions 1a and 1b)

In experiment 1, consistent with Prediction 1a and the small-victories approach, subjects performed in the ascending ordering 1.42 seconds per cell faster on average than in the descending ordering (significant at the 5% level), as shown in Table 1 (Panel I). This relationship does not substantially change when ascending is compared to the pooled results of both descending and even orders (1.23 seconds per cell faster on average, two-sided *p-value*: .019). Even subject performance falls between ascending and descending, which is inconsistent with Prediction 1b, but is consistent with Prediction 1a, suggesting post-subgoal factors dominate in this environment. A Kruskal-Wallis test indicates the differences for all three orders are significant at the 10% level (two-tailed *p-value*: .084). Both the Cuzick trend test and the Jonckheere-Terpstra test for ordered alternatives find the ascending-even-descending ordering to be significant, with *p-values* of .0260 and .0265 respectively.¹⁴ As a robustness check, a

¹⁴ We report two-tailed values whenever possible. Literally interpreting our predictions (ascending<even<descending) would result in the one-tailed *p-values* of .0130 and .0132 for the Cuzick trend test and the Jonckheere-Terpstra test for ordered alternatives, respectively.

regression (see Table 2) which controls for subject practice time does not appreciably change results. Additionally, time to complete each cell in seconds during the practice time is correlated with actual time in seconds with a coefficient of .133 and a standard error of .045 (results not tabled).

Table 1 (Panel II) shows the number of subjects that completed the full task, that is, those who copied all 150 cells in the 30-minute limit. A higher percentage of subjects (71%, 22 of 31) complete the task in ascending than descending (48%, 14 of 29) or even (58%, 18 of 31). A Pearson's chi-square test reveals this difference is meaningful at the 10% level. As before, this result is consistent with Prediction 1a, and the idea of post-subgoal factors dominating in this environment, but not consistent with Prediction 1b and the idea of pre-subgoal factors dominating.

Relative cell speed during task completion

A crucial assumption behind both Predictions 1a and 1b is that subjects complete cells at different speeds depending on their position within the columns that make up the general task. The validity of this assumption can be examined directly. Figure 2 shows subject performance for each ordering relative to average performance. Consistent with the pre-subgoal motivation of goal-gradient theories, subjects complete cells at a faster rate as they near the completion of a column. While subjects do not appear to start columns immediately faster, their time per cell greatly decreases over the course of completing columns, which is consistent with the post-subgoal motivation of social-cognitive theories. Further, note that this decrease is inconsistent with fatigue; subjects are speeding up over time.¹⁵ In results available in the web appendix and

¹⁵ Bonezzi, Brendl, and De Angelis (2011) find that for certain tasks performance is U-shaped: individuals exhibit the best performance at the beginning and end of a task, performing worse in the middle. As a quick look at Figures

discussed in more detail in our working paper (Brown and Lahey, 2014), we show that this apparent speed-up shown in the figures is statistically significant with a number of different specifications and assumptions.

As an overall trend, the results presented here are consistent with both pre- and post-subgoal motivation. While the results supported Prediction 1a and not Prediction 1b, this only means that the post-subgoal, social-cognitive factors were able to dominate the pre-subgoal in this environment. The relative support for the Corollary to Proposition 4 (descending orders being the worst performing) also is consistent with either Prediction. Our separate results on speeding up at the end of columns provide support for the validity of pre-subgoal motivation implied by goal-gradient theories. The support of Prediction 1a gives credence to the idea of the small victories strategy in task completion environments, in general.

Model Calibration

One of the advantages of the functional form chosen for our model in Equation (1) is the relative ease in which such a model can be calibrated and estimated. The model is not specific about the h and v functions, only requiring that they be non-decreasing and non-increasing, respectively. Following the general example of Olley and Pakes's (1996) empirical estimation of production functions—Equation (1) is effectively a production function—we estimate the h and v functions up to fourth-degree polynomials ($P = 4$). We estimate equation (1'),

$$\tau'_{ij} = \beta_1\mu + h(l) + v(k) + \gamma_j + \epsilon_{ij} \quad (1')$$

where $h(l) = \sum_{p=1}^P \beta_{p+1} l^p$ and $v(k) = \sum_{p=1}^P \beta_{P+p+1} k^p$ for $P=1, 2, 3, 4$.

2a-f demonstrates, we do not see an upside-down U-shape within each column. However, subjects appear to slow-down around cell 75, the middle of the task, regardless of treatment modality.

Here τ'_{ij} is the time it takes subject i to complete cell j , μ_i is a proxy for individual ability (in this case, the average time a subject completes a cell in the practice session), l is the number of cells remaining in the column, k is the number of previous columns completed, γ_j is a fixed effect term for every cell, and P is the degree of a simple polynomial.

Results from Equation (1') are presented in Table 3 and in the corresponding figures 3a and 3b of the estimated pre- and post-subgoal h and v functions. Figures 3a and 3b confirm the general monotonicity assumptions of our model. In all estimations of the post-subgoal v function it is decreasing; in all estimations of the pre-subgoal h function, with the exception of the domain of 5 to 10 cells remaining in the fourth-degree polynomial, the function is increasing. In the simple linear model, both terms are marginally significant ($p < 0.1$).¹⁶

Using the four calibrated models, we are able to make predictions of average cell completion times in any of the three orderings for any subject given his/her practice time. Table 4 provides estimates of average time to complete a cell for a subject with an average practice time (16.48 seconds/cell). In all four models, as shown in columns (2) through (5), a hypothetical subject with an average practice time should complete the ascending order in about 11.2 seconds/cell, the even order in 11.5 second/cell and the descending order in about 12 seconds/cell.¹⁷

The final two rows of Table 4 provide estimates to the average benefit of pre- and post-

¹⁶Local weighted regression (lowess) estimates of cells remaining and columns completed on time to complete cells show these general shapes even before controlling for the other variables and form of our general model. These figures are available in Web Appendix, Figure 1a and 1b.

¹⁷In reality, the gap between ascending and even orders (11.08 vs. 12.13) is greater than even and descending (12.13 vs. 12.5). However, this difference is not permitted in the model. The reason is that the ascending order has stronger post-subgoal factors, but weaker pre-subgoal factors than the even order (on average, ascending order cells have more columns completed but more cells remaining in a column than the even order), while the even order has both stronger pre- and post-subgoal factors than the descending order (on average, even order cells have more columns completed and less cells remaining in a column than the even order). To accommodate this theoretical property, the model expands the predicted difference between the descending and even orders and contracts the difference between the ascending and even orders.

subgoal factors. In the absence of the other factor, the post-subgoal (pre-subgoal) factor in column (2) says that ascending (even) subjects should complete a cell on average 0.391 seconds (0.059 seconds) faster relative to even (ascending) subjects, all else being equal. The net difference of 0.332 seconds is the predicted average time per cell an ascending order subject performs faster than an even subject. The total of both factors (0.45 seconds) is the predicted average time per cell an even order subject performs faster than a descending order subject. The predicted magnitude of the post-subgoal factors is greater than pre-subgoal factors (difference 0.332 in the linear specification from before, similar values in other specifications, and $p \approx 0.055$ in all specifications), a condition we call “dominance” in our model (see Theory section and Theoretical appendix for more detail).

Choice study

In a second study, 70 subjects were given the opportunity to choose their ordering. Table 5 shows the results of this choice. Of the 70 subjects, 16 chose ascending, 31 chose even and 23 chose descending. A Pearson’s chi-square test reveals these results are different from a random distribution at the 10% level. Here the ascending ordering—the method that follows the small victories theory and is shown to lead to the best performance among subjects in the initial study—is the least preferred. Less than one fourth of all subjects (22%) choose that method.¹⁸ This general trend is in contrast to Amar et al. (2011), who find that subjects prefer to pay debts from smallest to largest without considering interests rates, albeit in a very different choice problem. Their environment, unlike ours, transparently resembles debt repayment. One possibility is that subjects familiar with the debt-snowball strategies in the field incorrectly apply

¹⁸ The result is, however, reminiscent of Loewenstein and Prelec (1993) who find subjects prefer outcomes that improve over time provided those outcomes are explicitly defined as sequences.

it to their experiment. Our environment was designed specifically to abstract from the debt repayment problem so as not to evoke the popular debt-snowball heuristic.

Regression estimates suggest that the choice of ascending would help some participants more than others.¹⁹ Table 6 explores the effects of order on performance in the choice study for participants interacted with their answers to survey questions on self-control, critical reasoning skills, and risk aversion.²⁰ Participants with higher measures of self-control benefit more from ascending than from equal with a one-point increase in the self-control scale leading to a .139 second decrease in average cell time compared to those who chose equal, as shown in column (1). Similarly, participants with higher critical reasoning skills benefit more from the ascending choice than do other participants; a one-point increase in critical reasoning skills leads to a one second decrease in average cell time, with significance at the 10% level in column (2). Finally, the interaction between risk aversion and the choice of ascending is also negative; a one-point increase in risk aversion leads to a drop of .71 seconds on average cell time, also significant at the 10% level in column (3).

Extension to Field Debt-Reduction Environments

Our main result is that individuals increase their performance in tedious tasks when those tasks are broken down and put in ascending rather than descending order. When directly applied to the field, this suggests there is some benefit in using the small victories approach to debt reduction. While it will take substantial investigation to determine the actual magnitude of this

¹⁹ Although participants only participate in one condition, randomization allows us to use interaction terms in the regression analysis to present counterfactuals.

²⁰ We also control for practice time to make sure that the results are not being driven by differences in ability among the different choice orderings. There is little evidence this is the case. With the exception of suggestive evidence that types that choose ascending over descending are slightly more proficient at the typing task (10% level), we find no other significant correlations in the data. Another issue would be if survey answers were correlated with choice. With the exception of our risk aversion measure, which may predict the choice of ascending over equal at the 10% level in a multinomial logit, there is no significant difference between those who choose ascending and those who choose other orderings.

benefit in the field, we can project in what types of debt situations the small victories approach would be effective using the estimated benefit from our experiments.

In the initial study, subjects in the ascending ordering, on average, complete a cell in 11.08 seconds compared to 12.50 seconds in the descending ordering (as seen in Table 1, Panel I). Converted to rates, these values are 325 and 288 cells/hour, for ascending and descending, respectively. Thus, in terms of total performance, our results suggest subjects in the ascending ordering are about 13% more productive than descending.

We caution that these results should not be used to make definitive conclusions about debt-reduction situations without further analysis. The 13% figure is for illustrative purposes in order to show that there will be limits to the small victories approach. The actual number used is unimportant; for any number, there exists a difference in interest rates in which the small victory approach will not be beneficial. The following exercise illustrates how such a number could be used to determine the magnitude of the benefits of small victories for faster debt repayment compared to the draw-backs of a higher interest rate.

Suppose an individual has two \$10,000 outstanding loans. The first loan is at 10%, and the second has a rate between 10% and 20%. She may make monthly repayments of \$300²¹ on either loan. Suppose repaying the first loan first triggers the psychological motivations of small victories,²² and this individual is able to come up with 13% more on each payment, for a total payment of \$369.

Figure 4a shows the total difference in months to repay the two loans when following the

²¹ While this number was chosen somewhat arbitrarily, note that values much smaller than this (e.g., \$100) will never pay off either loan. Values much larger than this (e.g., \$1000) pay off the loan too quickly for interest to make much of a difference.

²² Without significantly changing our results, we could make the first loan worth \$9,999.99 and the second loan \$10,000.01 just to be consistent with the idea of ascending and descending orderings and the small victories approach. Changing the loan amounts more dramatically (e.g. \$5000/\$15000, \$7000/\$13000) slightly increases the benefit of the small victories approach.

small victories approach compared to the conventional method. In this example for all interest rates 16% and below, this individual would pay back both loans faster following the small victories method than the conventional economic method. But for rates 17% and higher, the conventional economic method of paying down debts with a higher rate of interest still produces faster debt repayment even though one is paying less per month.

Figure 4b shows the total amount spent on loans in both these cases. For rates 12% and lower, the additional psychological boost of the small victories and subsequent increase in debt repayment leads to a lower amount spent on loans than under the standard economic strategy. For rates between 13% and 16% inclusive, more is spent in total using the small victory method, but that is only when one includes the assumed \$69 boost each month from following that method. Depending on whether one believes that money would have been wasted or put to good use, the small victories method may or may not achieve a greater benefit for this individual. For values 17% and above, it is clear the individual is spending more on loans following the small victories method than the conventional method.

While the preceding is only an illustrative example—actual parameters in debt repayment situations vary greatly—the general lesson should be clear. Even if the small victories approach can give individuals the ability to save $x\%$ more on average, there is a limited range in which the difference between interest rates is overcome by the motivational boost. In general, this method works best when individuals have debts with similar interest rates. Similarly, bigger benefits will also accrue from larger differences in debt balances because of the motivational benefit from eliminating the smaller debt without the larger debt having as much time to accrue at the higher interest rate.

Discussion and Conclusion

We developed a formal model, based upon two strands of psychological literature, to explain the concept of “small victories,” that performance on a task can be increased by dividing it in smaller parts and completing those parts from smallest to largest. We find that if the post-subgoal motivational effects of one set, social-cognitive, dominate, ordering subtasks in ascending order of difficulty should produce optimal performance. Instead, if the pre-subgoal motivational effects of a competing set, goal-gradient theory, dominate, then dividing the task into equal lengths will produce optimal performance. In the initial study of this experiment, subjects who are randomly assigned to the small victories treatment (i.e., the ascending ordering), perform significantly faster and complete a higher percentage of tasks on average than in other orders. This result supports post-subgoal motivational idea of social-cognitive theories and affirms the general idea of small victories.

We find additional evidence for both of types of motivational factors and their corresponding psychological theories by directly examining our data. Subjects speed up at the ends of columns relative to their performance at the beginning of those columns, consistent with pre-subgoal motivation in goal-gradient theories. Additionally, our estimations find that past columns completed is positively correlated with performance, consistent with post-subgoal motivation in social-cognitive theories. As long as the post-subgoal motivational factors are present, Proposition 1 shows that in our environment subjects in ascending ordering should outperform those in the descending ordering. Further, the Corollary to Proposition 4 shows subjects in the even ordering should outperform those in the descending ordering. With both factors present, Proposition 4 shows that ascending subjects will outperform even subjects in this

environment if and only if post-subgoal factors dominate pre-subgoal. We conclude in our environment this must be the case.

Our model calibration provides further support of the existence of both factors. In all four specifications, the estimated, post-subgoal-motivation function, v , is decreasing and the estimated, pre-subgoal-motivation function, h , is almost always increasing. Further, by comparing predicted differences across treatments we can estimate the magnitude to which post-subgoal factors dominate pre-subgoal factors. In all four of our models, the former factors are greater than the latter (p -value \approx 0.055). Thus as we observe, the ascending order is predicted to be fastest, followed by the even order, followed by the descending.

There are limitations to this analysis. As mentioned previously, we caution readers in interpreting too much into our results concerning social-cognitive and goal-gradient theories. As an unintended consequence of our experimental design, we may have induced subjects to have “sub-subgoals.” Since there is no literature on either theory concerning this topic, we should not make any definitive conclusions about either theory. Additionally, our sample size is modest with ninety-one and seventy subjects for first and second studies, respectively, and we encourage replication.

Nonetheless, our results when interpreted via our theoretical model have a clear application to debt repayment. The increased motivational benefits of small victories may make it beneficial to pay off debts from smallest to largest in some cases, ignoring interest rates. This approach is identical to the debt-snowball approach suggested by some financial gurus, most notably Dave Ramsey (1998; 2009). It is in direct conflict with the traditional economic approach which advocates paying down debts from highest interest rate to lowest. However, as we demonstrate in our extension section, there are limits on when this approach will be effective.

The increase in motivation may not offset the additional interest accrued by not paying off the highest-interest-rate debts first if there are relatively different interest rates across debts.

Interestingly, when we allow a new set of subjects to choose which of the three orders they prefer, the ascending ordering is chosen least often. Our regression results indicate that the subjects who benefit most from the ascending ordering are subjects with the highest self-control and reasoning ability. This last finding may suggest a flaw with the debt snowball approach: the people who would benefit most from small victories may be the ones least likely to be in debt.²³ Obviously, future research will need to look at the issue more carefully, perhaps in more stylized debt-repayment scenarios or with surveys and actual field data.

Another possibility is that there is simply a difference between the option that allows an individual to perform best at a task and the option that an individual prefers. Our mathematical model has only focused on task performance, where it predicts ascending (or even) should lead to the best performance. While we do not use a preference or utility-based framework, such functions that would generate task performance functions seen in equation (1) (see footnote 3 for an example of such function) need not be at higher values for ascending or even orders. To see this intuition, note that a person may run his or her fastest 100 yards if chased by a tiger. This does not mean this method is the preferred way that one runs 100 yards; it likely is not. More research will need to be conducted to determine the appropriate form for the underlying functions that generate our task performance functions.

In apparent contrast to our results, Amar et al. (2011) find that people do not benefit from “small victories” and their subjects are most, rather than less, likely to choose the options similar

²³ Incekara-Hafalir and Linardi (2014) note that the Tangney et al. (2004) measure of self-control gives high scores to people who have self-control problems but who are not aware of their self-control problems. People with self-control problems may behave differently depending on whether or not they are aware of their self-control problems.

to the “small victories approach.” However, our designs differ in two key ways. First, their set-up does not allow for motivational boosts from small victories, whereas the primary purpose of our study is examine the validity of these motivational benefits. The second major difference is that our experiment is not framed as a debt-repayment strategy whereas theirs is, so participants in our study are not bringing with them pre-conceptions about the best ways to pay off debt. The “debt snowball” is a popular method of debt repayment that people may incorrectly apply to a stylized problem with debt-repayment context, but not in the absence of such context.

Although we motivate our theory and experiment with a debt-repayment example, debt-repayment is not the only domain that this “small victories” approach could aid people in reaching their long-term goals. A broader application would be consumer savings decisions. This approach may be equally valid when helping people to achieve work goals in an education or employment setting, or for health goals such as weight loss or physical training. All that is necessary is that a larger task be able to be broken down into smaller tasks of differing size.

Future research can explore the details of these different types of task completion. For example, in the debt repayment scenario, it can determine the full effects of framing debt in these situations. Adding additional factors to our experimental design, commonly found in debt-repayment scenarios, such as interest rates, minimum payments, ability to switch prepayments across debts, and actual cash values may aid in determining the appropriate bounds on the motivational improvement of the small victories method. Field experiments that randomly assign strategies to people with tasks that can be broken into subtasks are also a promising future direction.

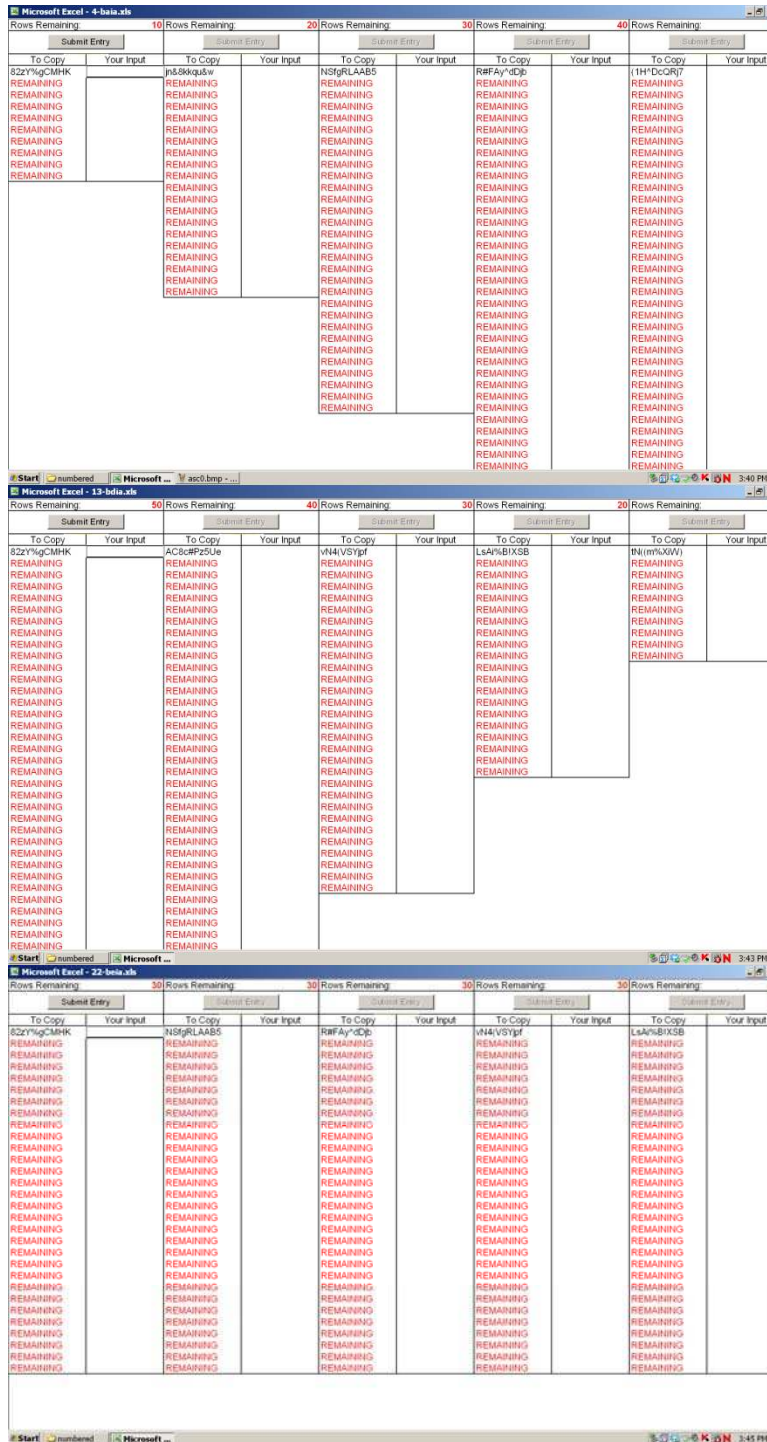
References

Amar, Moty, Dan Ariely, Shahar Ayal, Cynthia E. Cryder and Scott I. Rick. (2011) “Winning the

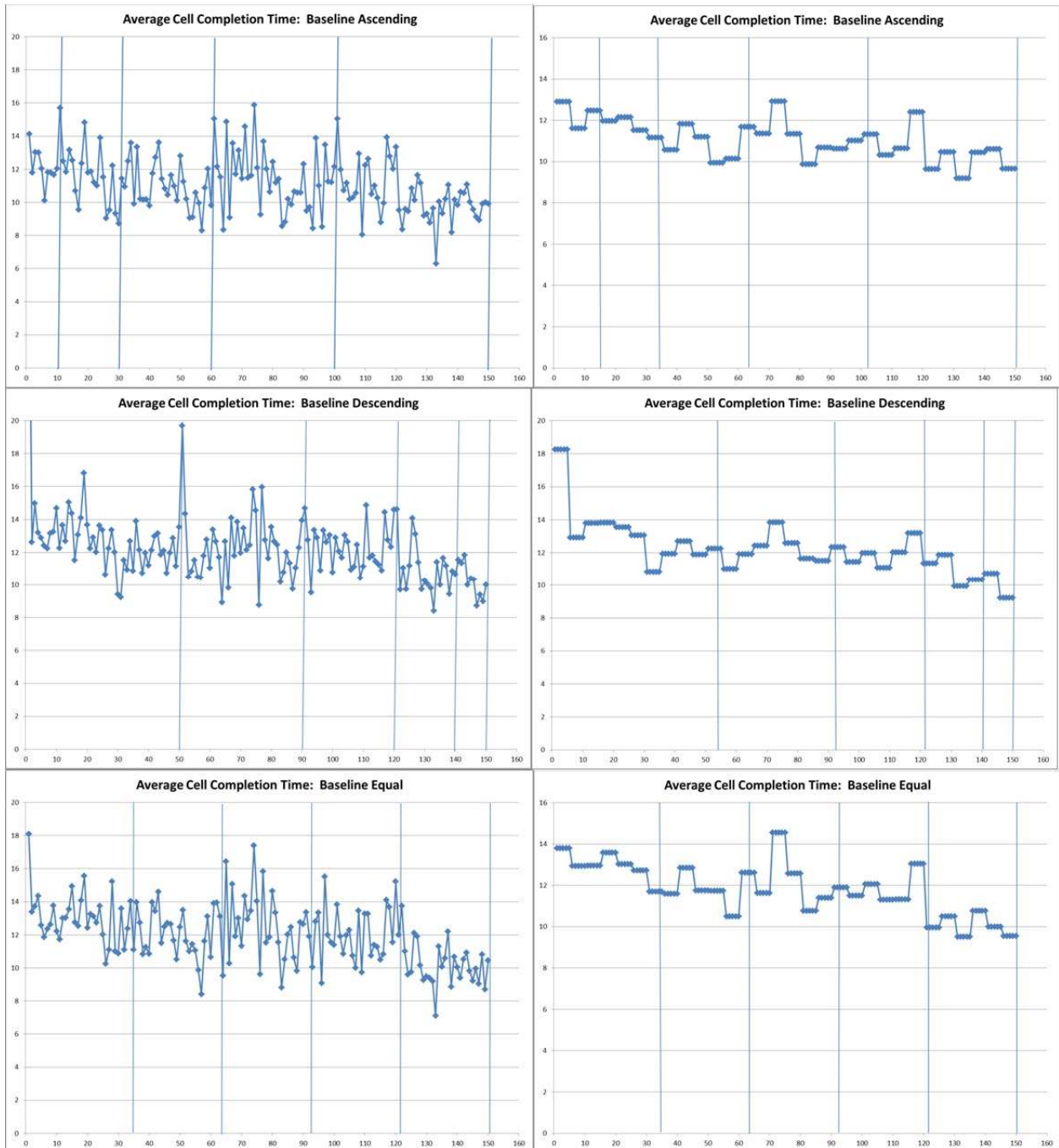
- Battle but Losing the War: The Psychology of Debt Management.” *Journal of Marketing Research*, 48(SPL): S38-S50.
- Amir, On and Dan Ariely. (2008). “Resting on Laurels: The Effects of Discrete Progress Markers as Subgoals on Task Performance and Preferences.” *Journal of Experimental Psychology*, 34(4): 1158-1171.
- Bandura, Albert. (1986). *Social Foundations of Thought and Action*. Englewood Cliffs, NJ: Prentice Hall.
- Bandura, Albert. (1977). *Social Learning Theory*. Englewood Cliffs, NJ: Prentice-Hall.
- Bandura, Albert and Dale H. Schunk. (1981). “Cultivating Competence, Self-Efficacy, and Intrinsic Interest through Proximal Self-Motivation.” *Journal of Personality and Social Psychology*, 41(3): 586-598.
- Bandura, Albert and Karen M. Simon. (1977). “The Role of Proximal Intentions in Self-Regulation of Refractory Behavior.” *Cognitive Therapy and Research*, 1(3): 177-193.
- Benabou, Roland and Jean Tirole. (2004) “Willpower and Personal Rules.” *Journal of Political Economy*, 112(4): 848-886.
- Bonezzi, Andrea, C. Miguel Brendl and Matteo De Angelis. (2011). “Stuck in the Middle: The Psychophysics of Goal Pursuit.” *Psychological Science*, 22(5): 607-612.
- Bricker, Jesse, Arthur B. Kennickell, Kevin B. Moore, and John Sabelhaus. (2012). “Changes in the U.S. Family Finances from 2007 to 2010: Evidence from the Survey of Consumer Finances.” *Federal Reserve Bulletin*, 98(2): 1-80.
- Brown, Alexander L., Zhikang Eric Chua, and Colin F. Camerer. (2009). “Learning and Visceral Temptation in Dynamic Saving Experiments.” *Quarterly Journal of Economics*, 124(1): 197-231.
- Brown, Alexander L. and Joanna N. Lahey. (2014) “Small Victories: Creating Intrinsic Motivation in Savings and Debt Reduction.” *National Bureau of Economic Research*, w20125.
- Eckel, Catherine. C. and Phillip J. Grossman (2008). “Forecasting Risk Attitudes: An Experimental Study Using Actual and Forecast Gamble Choices.” *Journal of Economic Behavior & Organization*, 68(1): 1-17.
- Fishbach, Ayelet., and Ravi Dhar. (2005). “Goals as Excuses or Guides: The Liberating Effect of Perceived Goal Progress on Choice.” *Journal of Consumer Research*, 32(3), 370-377.
- Fishbach, Ayelet., Ravi Dhar, and Ying Zhang. (2006). “Subgoals as Substitutes or Complements: the Role of Goal Accessibility.” *Journal of Personality and Social Psychology*, 91(2), 232-242.

- Frederick, Shane. (2005) "Cognitive Reflection and Decision Making." *Journal of Economic Perspectives*, 19(4): 25-42.
- Gal, David G. and Blakeley B. McShane. (2012). "Can Fighting Small Battles Help Win the War? Evidence from Consumer Debt Management." *Journal of Marketing Research*, 49(4): 487-501.
- Greiner, Ben. (2004). "The Online Recruitment System ORSEE 2.0." *Working Paper Series in Economics*, University of Cologne.
- Hadar, Josef and William R. Russell (1969). "Rules for Ordering Uncertain Prospects," *American Economic Review*, 59(1): 25-34.
- Heath, Chip, Richard P. Larrick, and George. Wu (1999) "Goals as Reference Points." *Cognitive Psychology* 38(1): 79-109.
- Heilizer, Fred. (1977). "A Review of Theory and Research on the Assumptions of Miller's Response Competitions Models: Response Gradients." *The Journal of General Psychology*, 97(1): 17-71
- Hull, Clark L. (1932). "The Goal Gradient Hypothesis and Maze Learning," *Psychological Review*, 39(1): 25-43.
- Incekara-Hafalir, Elif and Sera Linardi. (2014). "Self-Control and Awareness: Evidence from a Homeless Shelter." *Working Paper*.
- John, Oliver P., Laura P. Naumann, and Christopher J. Soto. (2008). "Paradigm Shift to the Integrative Big-Five Trait Taxonomy: History, Measurement, and Conceptual Issues." In: John, Oliver. P., Richard W. Robins, and Lawrence A. Pervin (Eds.). *Handbook of Personality: Theory and Research*. Guilford Press, New York, NY, 114-158.
- Kettle, Keri L., Remi Trudel, Simon Blanchard, and Gerald Haubl. (2014). "Debt Repayment Strategy and Consumer Motivation to Get Out of Debt." *Working paper*.
- Kivetz, Ran, Oleg Urminsky, and Yuhuang Zheng. (2006). "The Goal-Gradient Hypothesis Resurrected: Purchase Acceleration, Illusionary Goal Progress, and Customer Retention." *Journal of Marketing Research*, 43(1): 39-58.
- Latham, Gary P. and Gerard H. Seijts. (1999). "The Effects of Proximal and Distal Goals on Performance on a Moderately Complex Task." *Journal of Organizational Behavior*, 20(4): 421-429.
- Loewenstein, George F, and Drazen Prelec. (1993). "Preferences for Sequences of Outcomes." *Psychological Review*, 100(1): 91-108.
- Lusardi, Annamaria and Olivia S. Mitchell. (2014). "The Economic Importance of Financial Literacy: Theory and Evidence," *Journal of Economic Literature*, 52(1): 5-44.

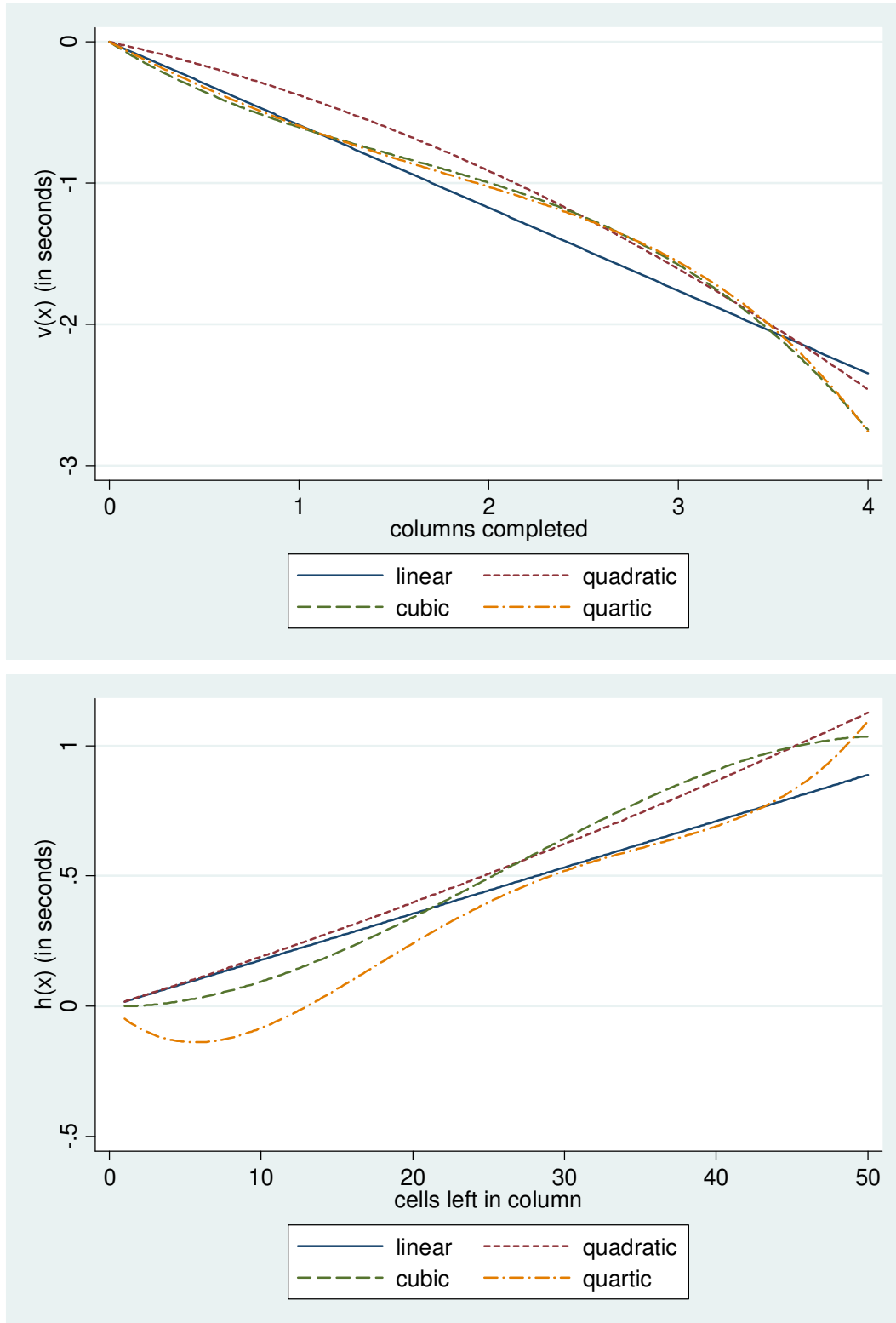
- Morgan, Mark. (1985). "Self-Monitoring of Attained Subgoals in a Private Study." *Journal of Educational Psychology*, 77(6): 623-630.
- Nunes, Joseph C. and Xavier Drèze. (2006). "The Endowed Progress Effect: How Artificial Advancement Increases Effort." *Journal of Consumer Research*, 32(4): 504-512.
- Olley, G. Steven and Ariel Pakes. (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64(6): 1263-1297.
- Patton, Jim. H., Matthew. S. Stanford, and Ernest S. Barratt. (1995). "Factor Structure of the Barratt Impulsiveness Scale." *Journal of Clinical Psychology*, 51(6): 768-774.
- Raab, Gerhard, Christian E. Elger, Michael Neuner, and Bernd Weber. (2011). "A Neurological Study of Compulsive Buying Behavior." *Journal of Consumer Policy*, 34(4): 401-413.
- Ramsey, Dave. (1998). *The Financial Peace Planner: A Step-by-Step Guide to Restoring Your Family's Financial Health*. New York: Penguin Books.
- Ramsey, Dave. (2009). *The Total Money Makeover: A Proven Plan for Financial Fitness*. Nashville, TN: Thomas Nelson.
- Rick, Scott I., Cynthia E. Cryder, and George Loewenstein. (2008). "Tightwads and Spendthrifts." *Journal of Consumer Research*, 34(6): 767-782.
- Rothschild, Michael and Joseph E. Stiglitz. (1970). "Increasing Risk: I. A Definition." *Journal of Economic Theory*, 2(3): 225-243.
- Stock, Jennifer and Daniel Cervone. (1990). "Proximal Goal Setting and Self-Regulatory Processes." *Cognitive Therapy and Research*, 14(5): 483-489.
- Tangney, June P., Roy F. Baumeister and Angie Luzio Boone. (2004). "High Self-Control Predicts Good Adjustment, Less Pathology, Better Grades and Intrapersonal Success." *Journal of Personality*, 72(2): 272-322.
- Zuckerman, M. (1994). *Behavioral Expressions and Biosocial Bases of Sensation Seeking*. Cambridge, Cambridge, University Press.



Figures 1(a-c): The experiment interface featured a task of typing 150 lines of ten character text in a Microsoft Excel Spreadsheet. Figures (a, top),(b, middle), and (c, bottom) show the task with five columns in ascending, descending, and even orderings, respectively.



Figures 2(a)-(f): Average Cell Completion Time by Cell. Note: In (b), (d), and (f), each group of five cells has been given the average completion time for that group for readability purposes and to smooth outliers.



Figures 3a and 3b: Estimated post-subgoal- ($v(x)$, above) and pre-subgoal- ($h(x)$, below) motivation functions from model calibration of first- to fourth-degree polynomial specifications.

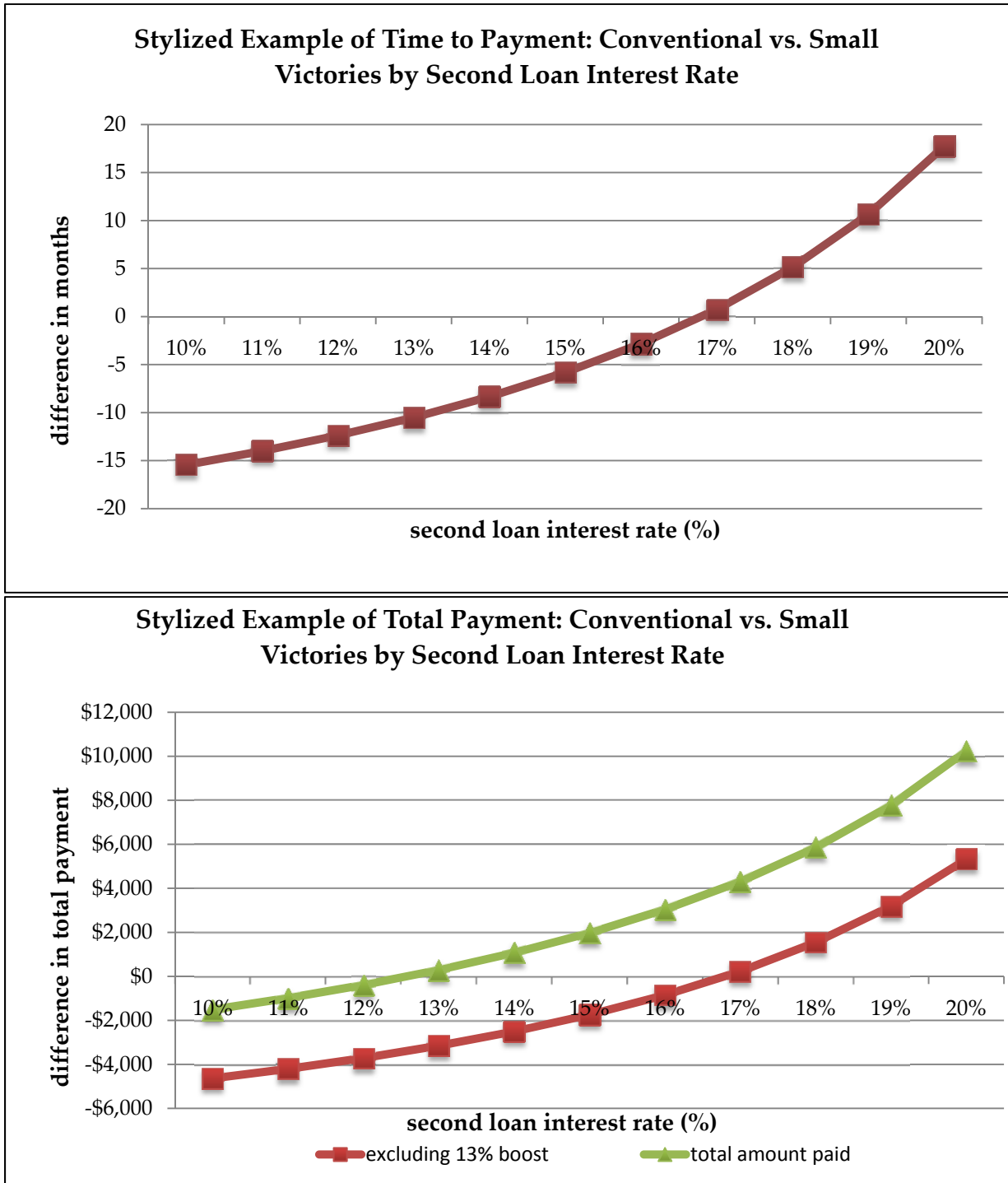


Figure 4a (above): Difference in total time to pay off two loans with one loan at 10% interest and the other at 10%-20%. The standard monthly payment is \$300, but the small victories method produces a 13% boost corresponding to a \$369 monthly payment. 4b (below): Difference in total amount spent to pay off two loans with one loan at 10% interest and the second at 10%-20%. The standard monthly payment is \$300, but the small victories method produces a 13% boost corresponding to a \$369 monthly payment. One line shows the total amount spent on the loan, the other shows that amount without the 13% boost (i.e., the extra \$69 each month).

Table 1: Main Results

Panel I: Time to completion				
	Mean (in sec)	N	Asc Difference	p (two- sided)
Ascending	11.08	31		
Not Ascending	12.31	60	1.23	0.019
Even	12.13	31	1.05	0.078
Descending	12.50	29	1.42	0.015
Kruskal Wallis				0.084
Panel II: Completion as an outcome				
Ascending		0.13248 (0.1222)		
Descending		-0.0963 (0.1280)		
Observations		91		
Asc-dsc chi squared p-value		0.08		

Notes: Results in Panel I from separate t-tests on the time to complete each cell in seconds. Panel II provides marginal effects results from a probit regression on whether or not the participant completed the 150 cell task. In Panel II the omitted variable is even.

Table 2

Average time to complete cells		
	(1)	(2)
Ascending	-1.0522* (0.5862)	-0.9640* (0.5518)
Descending	0.3718 (0.6496)	0.0464 (0.5888)
Practice average		0.1266*** (0.0439)
Observations	91	90
Asc-dsc F-test	0.01	0.05

Notes: Robust standard errors in parentheses. F-test value given is for the p-value of the F-statistic. Omitted ordering is equal. One student had technical difficulties with the practice session and is dropped from regressions that control for practice average. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Calibrating the Model: Time to Complete Cell (in Seconds)

	(1)	(2)	(3)	(4)
Practice Time (in Seconds)	0.1166*** (0.0390)	0.1165*** (0.0391)	0.1165*** (0.0391)	0.1165*** (0.0391)
Columns Completed	-0.5867* (0.2974)	-0.2972 (0.2655)	-0.8424** (0.4053)	-0.6841 (0.5825)
Columns Completed Squared		-0.0793* (0.0461)	0.3058* (0.1831)	0.0701 (0.6213)
Columns Completed Cubed			-0.0667** (0.0311)	0.0335 (0.2526)
(Columns Completed)^4				-0.0128 (0.0321)
Cells Left in Column	0.0178* (0.011)	0.0181 (0.0221)	-0.0013 (0.0397)	-0.0538 (0.1046)
Cells Left in Column Squared		0.0001 (0.0005)	0.0012 (0.0020)	0.0061 (0.0098)
Cells Left in Column Cubed			0.0000 (0.0000)	-0.0002 (0.0003)
(Cells Left in Column)^4				0.0000 (0.0000)
Cell Fixed Effects?	Y	Y	Y	Y
Observations	12,694	12,694	12,694	12,694
R-squared	0.858	0.858	0.858	0.858
Joint F-test Results (p-value)				
Columns completed	0.0516	0.1014	0.0552	0.1008
Cells Left	0.0982	0.1707	0.2089	0.2510

Notes: Results from Equation 1'. Standard errors are clustered on cell.

Table 4: Predictions from the Calibration

	actual	linear	quadratic	cubic	quartic
	(1)	(2)	(3)	(4)	(5)
ascending	11.08	11.213 (0.260)	11.203 (0.261)	11.188 (0.264)	11.184 (0.265)
even	12.13	11.545 (0.188)	11.534 (0.194)	11.529 (0.195)	11.536 (0.193)
descending	12.5	11.995 (0.286)	12.022 (0.290)	12.050 (0.293)	12.047 (0.293)
goal-gradient		-0.059	-0.078	-0.090	-0.080
pre-subgoal factors		(0.0354)	(0.035)	(0.052)	(0.061)
social-cognitive		-0.391	-0.410	-0.431	-0.432
post-subgoal factors		(0.198)	(0.198)	(0.204)	(0.207)

Note: Predicted times for ascending, even, and descending in columns (2)-(5) are for a hypothetical participant with average practice times. The difference between the predicted ascending and even times is the net of the post-subgoal factors and pre-subgoal factors. The difference between the predicted even and descending times is the total of both factors. Solving this system of equations provides individual estimates on both factors.

Table 5: What they chose

	N	Mean (in sec)
Ascending	16	10.85
Not Ascending	54	11.20
Even	31	11.03
Descending	23	11.44

chi-squared p-value 0.09

Notes: Results from the choice study.

Table 6: Effect of choice interactions with survey data on average cell time

	Self-control	Cognitive Reflection	Risk Aversion
	(1)	(2)	(3)
X*ascending	-0.139* (0.070)	-1.060* (0.586)	-0.710* (0.390)
X*descending	-0.026 (0.062)	-0.735* (0.401)	-0.410 (0.317)
ascending	6.333* (3.280)	0.825 (0.793)	2.495 (1.599)
descending	1.241 (2.600)	0.935 (0.663)	1.178 (1.013)
X	-0.011 (0.046)	0.073 (0.231)	0.188 -0.174
practice average	0.257*** (0.068)	0.253*** (0.070)	0.274*** (0.069)
Observations	64	64	64

Notes: Outcome is average time to complete one cell in seconds. X is the Tangney-Baumeister measure of self-control in column (1) and the Cognitive Reflection Task in Column (2). Robust standard errors in parentheses. Omitted ordering is "equal". Six people with random survey malfunctions were eliminated from these regressions. *** p<0.01, ** p<0.05, * p<0.1

A Theoretical Appendix

Let us define a task, X , that consists of individual discrete elements $x \in X$. Each task X can be framed into subgoals using a partition α .¹

Definition. *The subgoal partition $\alpha \in A(X)$ is a list of m ordered sets $\alpha = (\alpha_1, \dots, \alpha_k, \dots, \alpha_m)$ where $m \leq |X|$. For each $1 \leq k \leq m$, $\alpha_k = (\alpha_{kl})$ for $1 \leq l \leq |\alpha_k|$, such that*

$$\sum_{k=1}^m |\alpha_k| = |X| \quad \text{and} \quad \bigcup_{k=1}^m \bigcup_{l=1}^{|\alpha_k|} \alpha_{kl} = X.$$

Note that this implies that no two x 's are repeated in α .

The time it takes each individual $i \in N$ to complete a task, X , will be the sum of the time it takes to complete each element, x .² This time will strictly depend on each element's position in the subgoal partition. The two factors that may matter in the subgoal partition are the number of remaining elements in the subgoal, and the number of previously completed subgoals. These factors will additively affect time performance for each individual. The function $\tau_i(x, \alpha)$ gives the time it takes individual i to complete element x under subgoal partition α .

$$\tau_i(x, \alpha) = \tau_i(\alpha_{kl}) = \mu_i + h(|\alpha_k| - l) + v(k) + \gamma_w + \epsilon_{i\alpha_{kl}}.$$

where $w = \sum_{r=1}^{k-1} |\alpha_r| + l$, $x = \alpha_{kl}$ and k and l indicate element x 's position in subgoal partition α .

There are other terms in this equation not related to the two factors. The term γ_w represents any error with element x being the w th element completed in X , independent of partition. The term μ_i represents individual characteristics and $\epsilon_{ix} = \epsilon_{i\alpha_{kl}}$ represents personal idiosyncratic error with element x . It is helpful to impose some conditions on this latter error term, namely it does not vary by partition.

Assumption A.1. *The personal idiosyncratic error term for element x is independent of partition. That is, for any element in any task, $x \in X$, for any $\alpha, \alpha' \in A(X)$, if $x = \alpha_{kl} = \alpha'_{k'l'}$, then $\epsilon_{i\alpha_{kl}} = \epsilon_{ix} = \epsilon_{i\alpha'_{k'l'}}$.*

Assumption A.1 requires that any variation in performance due to an element's position in subgoal partition is expressed in the terms h and v . Function h expresses how the position of an element within a subgoal affects performance, specifically its

¹In debt-repayment, one could think of each x as a monthly payment, and each subgoal as an individual debt. The task X would be the removal of all debt. In our experiment each element is a cell, each subgoal in a column, and X is a session.

²Alternatively one could say the total cost to complete task X is the sum of the individual costs paid to complete each element x .

position from the end of a subgoal. Function v expresses how previously completed subgoals affect performance. Note that the total time it takes individual i to complete a task under subgoal partition α is given by

$$T_i(\alpha) = \sum_{x \in X} \tau_i(x, \alpha) = C_i + \sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} h(|\alpha_k| - l) + v(k).$$

where $C_i = \sum_{x \in X} \mu_i + \gamma_w + \epsilon_{i\alpha_{kl}}$. Since each term μ_i , γ_w , and $\epsilon_{i\alpha_{kl}}$ is independent of partition, their total over X is constant for each subgoal partition.

Using the social-cognitive (Bandura, 1977; 1986) and goal-gradient theories (Heilizer 1977; Hull 1932) within psychological literature as our guide, we will impose restrictions on functions h and v .

Assumption A.2 (post-subgoal motivation). *After completing a subgoal, individual performance does not decrease. That is, costs or time do not increase with successive subgoals. Formally, v is non-increasing.*

Often subgoals may be already defined, and one may be concerned with the question of how to order the subgoals in a way that will increase performance. For instance, a consumer may have multiple debts owed, and can choose in which order to repay them, but cannot restructure the debts. To fit such cases, we define a class of subgoal partitions, or all subgoal partitions that have the same structure of elements in each subgoal, but the order of the subgoals has been changed.

Definition. *For any given X , the subgoal partitions α' and α'' are said to be in the same class of subgoal partitions, $\beta \subseteq A(X)$, if and only if $|\alpha'| = |\alpha''| = m$ and for all k , $1 \leq k \leq m$, there exists a k' such that $\alpha'_k = \alpha''_{k'}$. That is, β is the set of all subgoal partitions that differ by at most the ordering of subgoals.*

Under assumption A.2 we can deduce a general result about the aggregate performance of tasks under subgoal partitions of the same class. To prove the result a helpful lemma is necessary. The lemma is very similar to a standard result of expected utility theory involving first-order stochastic dominance. The proof follows the work of Hadar and Russell (1969), and the more well-known, Rothschild and Stiglitz (1970).

Lemma. *Suppose there are a finite number of distinct values, $j = 1, 2, \dots, n$, $y_{j'} > y_j$ if and only if $j' > j$. Define functions f and g so $f(y_j) = a_j$ and $g(y_j) = b_j$, where $0 \leq a_j, b_j \leq 1$ and $\sum_{j=1}^n f(y_j) = \sum_{j=1}^n g(y_j) = 1$. Further define*

$$F(y_j) = \sum_{r=1}^j f(y_r) \quad \text{and} \quad G(y_j) = \sum_{r=1}^j g(y_r). \quad (\text{A.1})$$

For any non-increasing function, $u : \mathbb{R} \rightarrow \mathbb{R}$, where u is continuous over $[y_1, y_n]$, and differentiable over all open intervals (y_j, y_{j+1}) for $1 \leq j \leq n - 1$. If $G(y_j) \leq F(y_j)$ for $1 \leq j \leq n$ then

$$\sum_{j=1}^n u(y_j)g(y_j) \leq \sum_{j=1}^n u(y_j)f(y_j). \quad (\text{A.2})$$

The conditions, u is non-constant and $G(y_j) < F(y_j)$ for $1 \leq j \leq n - 1$, or u is strictly decreasing and g and f are different, both imply (A.2) with strict inequality.

Proof. This proof is largely derived from Hadar and Russell (1969), Theorem 1, and is similar to many others involving first-order stochastic dominance.

For every interval $[y_j, y_{j+1}]$ for $1 \leq j < n$, the Mean Value Theorem shows there exists a $y_j < \xi_j < y_{j+1}$ such that

$$u(y_j) = u(y_{j+1}) - u'(\xi_j)\Delta y_j \quad \text{where} \quad \Delta y_j = y_{j+1} - y_j.$$

Then

$$\begin{aligned} \sum_{j=1}^n u(y_j)f(y_j) - \sum_{j=1}^n u(y_j)g(y_j) &= \sum_{j=1}^n \left[u(y_n) - \sum_{r=j}^{n-1} u'(\xi_r)\Delta y_r \right] (f(y_j) - g(y_j)) \\ &= \sum_{j=1}^n u(y_n) (f(y_j) - g(y_j)) \\ &\quad - \sum_{j=1}^n \sum_{r=j}^{n-1} u'(\xi_r)\Delta y_r (f(y_j) - g(y_j)) \\ &= u(y_n) \left[\sum_{j=1}^n f(y_j) - \sum_{j=1}^n g(y_j) \right] \\ &\quad - \sum_{j=1}^n \left[(f(y_j) - g(y_j)) \sum_{r=j}^{n-1} u'(\xi_r)\Delta y_r \right] \\ &= - \sum_{r=1}^{n-1} \sum_{j=1}^r (f(y_j) - g(y_j)) u'(\xi_r)\Delta y_r \\ &= - \sum_{r=1}^{n-1} u'(\xi_r) (F(y_r) - G(y_r)) \Delta y_r \\ &\geq 0. \end{aligned}$$

By definition, $\Delta y_r > 0$. Non-increasing implies $u'(\xi_r) \leq 0$. With $G(y_r) \leq F(y_r)$, our final result is greater than or equal to 0. If instead, u is strictly decreasing and g and f are different, this implies $u'(\xi_r) < 0$ and that there is some j' where $G(y_{j'}) < F(y_{j'})$. In

such case, we have strict inequality. Similarly, if u is non-constant and $G(x_j) < F(x_j)$ for all for $1 \leq j < n$, there is some j' where $u'(\xi_{j'}) < 0$. In such case we also would have strict inequality. \square

Proposition 1 (small victories). *For any i , for a given class of subgoal partitions, $\beta \subseteq A(X)$. Define an ascending ordering, α' where*

$$|\alpha'_1| \leq \dots \leq |\alpha'_k| \leq \dots \leq |\alpha'_m|,$$

and a descending ordering where

$$|\alpha''_1| \geq \dots \geq |\alpha''_k| \geq \dots \geq |\alpha''_m|.$$

Then for any $\alpha \in \beta$,

$$T_i(\alpha') \leq T_i(\alpha) \leq T_i(\alpha'').$$

If v is non-constant, and all the subgoals in β are not of the same length, $T_i(\alpha') < T_i(\alpha'')$.

Proof. Choose any $\alpha, \alpha', \alpha'' \in \beta$. First we will show that for a class of subgoal partitions, for any $\alpha \in \beta$, the value $\sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} h(|\alpha_k| - l)$ is equal. Consider any $x^* \in X$. Since all subgoal partitions defined on X must contain one unique x^* , let us define $\alpha_{kl} = x, \alpha'_{k'l'} = x$, and $\alpha''_{k''l''} = x$, where $\alpha_{kl} \in \alpha, \alpha'_{k'l'} \in \alpha', \alpha''_{k''l''} \in \alpha''$. Since $\alpha, \alpha', \alpha''$ are all in the same class of subgoal partitions, by definition the ordered sets $\alpha_k, \alpha'_{k'}, \alpha''_{k''}$ must be equal. It follows that

$$\sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} h(|\alpha_k| - l) = \sum_{k=1}^m \sum_{l=1}^{|\alpha'_k|} h(|\alpha'_k| - l) = \sum_{k=1}^m \sum_{l=1}^{|\alpha''_k|} h(|\alpha''_k| - l).$$

Next we will define the following functions.

$$\bar{v}(y) = \begin{cases} v(y) & \text{if } y \in \mathbb{Z}, \\ ([y] - y)v(\lfloor y \rfloor) + (y - \lfloor y \rfloor)v(\lceil y \rceil) & \text{otherwise.} \end{cases} \quad (\text{A.3})$$

$$f_\alpha(k) = \begin{cases} |\alpha_k| / \sum_{j=1}^m |\alpha_j| & \text{if } k = 1, 2, \dots, m, \\ 0 & \text{otherwise.} \end{cases} \quad (\text{A.4})$$

It follows that $0 \leq f_\alpha(k), f_{\alpha'}(k), f_{\alpha''}(k) \leq 1$ for $k = 1, 2, \dots, m$. Additionally $\sum_{k=1}^m f_\alpha(k) = \sum_{k=1}^m f_{\alpha'}(k) = \sum_{k=1}^m f_{\alpha''}(k) = 1$. Note also that \bar{v} is continuous. It is differentiable over every open interval between integers. It is also non-increasing by Assumption A.2.

Define $F_\alpha(n) = \sum_{k=1}^n f_\alpha(k)$ and $F_{\alpha'}, F_{\alpha''}$ in the same way. Note that for any $1 \leq n < m$, $F_{\alpha'}(n)$ and $F_{\alpha''}(n)$ contain the sums of the lengths of the n shortest

subgoals and the n longest subgoals, respectively. Thus $F_{\alpha'}(n) \leq F_{\alpha}(n) \leq F_{\alpha''}(n)$. If all the subgoals are not of the same length, $F_{\alpha'}(n) < F_{\alpha''}(n)$.

By our Lemma, $\sum_{j=1}^m f_{\alpha'}(j)\bar{v}(j) \leq \sum_{j=1}^m f_{\alpha}(j)\bar{v}(j) \leq \sum_{j=1}^m f_{\alpha''}(j)\bar{v}(j)$ which implies

$$\sum_{k=1}^m \sum_{l=1}^{|\alpha'_k|} v(|\alpha'_k|) \leq \sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} v(|\alpha_k|) \leq \sum_{k=1}^m \sum_{l=1}^{|\alpha''_k|} v(|\alpha''_k|).$$

Since the other terms in T_i are independent of the subgoal partition or already shown to be constant in summation, we have $T_i(\alpha') \leq T_i(\alpha) \leq T_i(\alpha'')$. If all the subgoals are not of the same length, we would have $F'_{\alpha}(n) < F''_{\alpha}(n)$ for $1 \leq n < m$, so by our Lemma, we would have $T_i(\alpha') < T_i(\alpha'')$. \square

Proposition 1 states that if people perform better after completing a subgoal, and only the ordering of subgoals can be changed, putting subgoals in ascending order leads to optimal performance (or, equivalently, minimal costs), while descending order leads to the worst performance (or, equivalently, maximal costs). As long as all subgoals are not of equal length there should be a difference between these two extremes.

Note that Proposition 1 requires no structure on function h , the function that concerns performance relative to the end of the subgoal. Thus, the findings of social-cognitive theories, when applied to our model, suggest an optimal debt-repayment (or any general task-completion strategy) that is consistent with the debt snowball (or small victories) approach.

We now consider the goal-gradient hypothesis and corresponding restrictions it places on function h . The theory suggests distance to the end of a subgoal affects performance.

Assumption A.3 (pre-subgoal motivation). *As individuals move closer to the end of a subgoal, their performance does not decrease. That is, costs or time do not increase the closer one comes to the end of a subgoal. Formally, h is non-decreasing.*

If the pre-subgoal term, h is all that matters, and the post-subgoal term v is constant (effectively zero), we have a much different result about the optimal structure of subgoal partitions.

Proposition 2. *Suppose v is constant. Then for any X , i , and m , if there exists an even ordering, $\alpha' \in A(X)$ such that $|\alpha'_k| = c$ for all $1 \leq k \leq m$, then*

$$T_i(\alpha') \leq T_i(\alpha) \quad \forall \alpha \in A(X) \text{ where } |\alpha'_k| = |\alpha_k| = m.$$

Further, if all the subgoals in α are not of the same length and h is strictly increasing, $T_i(\alpha') < T_i(\alpha)$.

Proof. Choose any $\alpha \in A(X)$. If v is constant, the only term in T_i that changes with α is h . We must show

$$\sum_{k=1}^m \sum_{l=1}^{|\alpha'_k|} h(|\alpha'_k| - l) \leq \sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} h(|\alpha_k| - l), \quad (\text{A.5})$$

with strict inequality if all the subgoals in α are not of the same length and h is strictly increasing. Next we will define the following functions.

$$\bar{h}(y) = \begin{cases} h(y) & \text{if } y \in \mathbb{Z}, \\ ([y] - y)h(\lfloor y \rfloor) + (y - \lfloor y \rfloor)h(\lceil y \rceil) & \text{otherwise.} \end{cases} \quad (\text{A.6})$$

$$g_\alpha(n) = \begin{cases} |\{\alpha_{kl} \in \alpha : |\alpha_k| - l = n\}| / |X| & \text{if } n = 0, 1, 2, \dots \\ 0 & \text{otherwise.} \end{cases} \quad (\text{A.7})$$

Let l^* be the length of the longest subgoal in either α or α' . It follows that $0 \leq g_\alpha(n), g_{\alpha'}(n) \leq 1$ for $n = 1, 2, \dots, l^* - 1$. Additionally $\sum_{n=0}^{l^*-1} g_\alpha(n) = \sum_{n=0}^{l^*-1} g_{\alpha'}(n) = 1$. Note also that $-\bar{h}$ is continuous. It is differentiable over every open interval between integers. The function, $-\bar{h}$, is also non-decreasing by Assumption A.3.

Define $G_\alpha(n) = \sum_{k=1}^n g_\alpha(k)$ and $G_{\alpha'}$ in the same way. Note that for every $n = 0, 1, 2, \dots, c - 1$, the function $g_{\alpha'}(n) = m / |X|$. Since there are only m subgoals, we must have $g_\alpha(n) \leq m / |X|$. Then $G_\alpha(n) \leq G_{\alpha'}(n)$ for $n = 0, 1, 2, \dots, c - 1$. Since $G_{\alpha'}(c - 1) = 1$, $G_\alpha \leq G_{\alpha'}$. If α contains subgoals of different lengths, let l' be the length of the shortest subgoal in α . Then $g_\alpha(l') < m / |X|$, so g_α and $g_{\alpha'}$ are different.

By our Lemma, $\sum_{n=1}^{l^*-1} g_{\alpha'}(j) (-\bar{h}(j)) \leq \sum_{n=1}^{l^*-1} g_\alpha(j) (-\bar{h}(j))$ which implies (A.5). If all the subgoals in α are not of the same length, we have already shown g_α and $g_{\alpha'}$ are different. If in addition, h is strictly increasing, then we have $\sum_{n=1}^{l^*-1} g_{\alpha'}(j) (-\bar{h}(j)) < \sum_{n=1}^{l^*-1} g_\alpha(j) (-\bar{h}(j))$ which implies (A.5) with strict inequality. \square

An similar statement can be made about ascending orderings.

Proposition 3. *Suppose h is constant. Then for any X , i , and m , there exists a subgoal partition $\alpha' \in A(X)$, in ascending order, $|\alpha'_1| \leq \dots \leq |\alpha'_k| \leq \dots \leq |\alpha'_m|$, for all $1 \leq k \leq m$, such that*

$$T_i(\alpha') \leq T_i(\alpha) \quad \forall \alpha \in A(X) \text{ where } |\alpha'| = |\alpha| = m.$$

Further, if α is not ascending and v is strictly decreasing, $T_i(\alpha') < T_i(\alpha)$.

Proof. Choose any $\alpha \in A(X)$. Consider the ascending subgoal partition $\hat{\alpha}$ where $|\hat{\alpha}_k| = 1$ for all $k < m$ and $|\hat{\alpha}_m| = |X| - m + 1$. Define functions $\bar{v}(y)$ and $f_\alpha(k)$ as in (A.3) and (A.4). It follows that $0 \leq f_\alpha(k), f_{\hat{\alpha}}(k) \leq 1$ for $k = 1, 2, \dots, m$. Additionally $\sum_{k=1}^m f_\alpha(k) = \sum_{k=1}^m f_{\hat{\alpha}}(k) = 1$. Note also that \bar{v} is continuous. It is

differentiable over every open interval between integers. It is also non-increasing by Assumption A.2.

Define $F_\alpha(n) = \sum_{k=1}^n f_\alpha(k)$ and $F_{\hat{\alpha}}$ in the same way. Note that for any $k < m$, $f_{\hat{\alpha}}(k) = 1/|X|$. Since every subgoal must contain at least one element and there are m subgoals, $1/|X| \leq f_\alpha(k) \leq (|X| - m + 1)/|X|$. It follows that $F_{\hat{\alpha}} \leq F_\alpha$. If α is not ascending, there exist k' and k'' such that $k' < k''$ and $|\alpha_{k'}| > |\alpha_{k''}|$. We have $k' < m$ and $|\alpha_{k'}| > 1$. Then $f_\alpha(k') > f_{\hat{\alpha}}(k')$, and f_α and $f_{\hat{\alpha}}$ are different.

By our Lemma, $\sum_{j=1}^m f_{\hat{\alpha}}(j)\bar{v}(j) \leq \sum_{j=1}^m f_\alpha(j)\bar{v}(j)$ which implies $\sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} v(|\alpha'_k|) \leq \sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} v(|\alpha_k|)$. Since the other terms do not differ from $\hat{\alpha}$ to α , it follows that $T_i(\alpha') \leq T_i(\alpha)$. If α is not ascending, we have already shown f_α and $f_{\hat{\alpha}}$ are different. If in addition, v is strictly decreasing, our Lemma implies $\sum_{j=1}^m f_{\hat{\alpha}}(j)\bar{v}(j) < \sum_{j=1}^m f_\alpha(j)\bar{v}(j)$. By identical reasoning, we would have $T_i(\alpha') < T_i(\alpha)$. \square

It should be noted that the proceeding two Propositions, unlike Proposition 1, apply to all subgoals partitions possible under X , not just rearrangements of subgoals. However, they require stronger restrictions about our functions h and v than our Proposition 1. Specifically, each requires that one of the functions be constant. Under such assumptions, Propositions 2 and 3 provide two different answers on which ordering, ascending or even, is optimal.

The remainder of this section will be concerned with developing general definitions and a proposition about optimal orderings when both pre- and post-subgoal motivational forces are present. First, we need a general way to compare the effects of the two terms.

Definition. For any two subgoal partitions $\alpha, \alpha' \in A(X)$, with $|\alpha| = |\alpha'| = m$, for the following relation,

$$\left| \sum_{k=1}^m (|\alpha_k| - |\alpha'_k|) v(k) \right| - \left| \sum_{k=1}^m \sum_{l=1}^{|\alpha_k|} h(|\alpha_k| - l) - \sum_{l=1}^{|\alpha'_k|} h(|\alpha'_k| - l) \right| \begin{matrix} \geq \\ \leq \end{matrix} 0, \quad (\text{A.8})$$

we say the post-subgoal factors dominate the pre-subgoal factors if and only if (A.8) is greater than 0. Alternatively the pre-subgoal factors dominate the post-subgoal factors if (A.8) is less than 0. There is no dominance between pre- and post-subgoal factors if and only if (A.8) is equal to 0.

Next, we need to restrict our focus to tasks where both types of orderings are possible.

Definition. Consider any X with $\alpha^e, \alpha^a, \alpha^d \in A(X)$ where $\alpha^e, \alpha^a, \alpha^d$ are even, ascending, and descending orderings, respectively. Further restrict α^a and α^d to be in the same class of subgoal partitions, and α^e to have the same number of ordered sets as α^a and α^d . That is, there exists a β such that $\alpha^a, \alpha^d \in \beta$ and $|\alpha^e| = |\alpha^a| = |\alpha^d| = m$. We refer to any set $\{\alpha^e, \alpha^a, \alpha^d\}$ as a Δ -set.

Note that a given Δ -set may not be unique for a given task X or even a given number of subgoals m . Since our experiment involves a particular Δ -set, we find it useful to make comparisons across the three subgoal partitions.

Proposition 4. *For a given Δ -set, $\{\alpha^a, \alpha^d, \alpha^e\}$, where all the subgoals in α^a are not of the same length, for any i ,*

1. $T_i(\alpha^a) < T_i(\alpha^e)$ if and only if post-subgoal factors dominate pre-subgoal factors.
2. $T_i(\alpha^a) > T_i(\alpha^e)$ if and only if pre-subgoal factors dominate post-subgoal factors.
3. $T_i(\alpha^a) = T_i(\alpha^e)$ if and only if there is no dominance between pre- and post-subgoal factors.

Proof. For a given i , $T_i(\alpha^a) - T_i(\alpha^e) =$

$$\sum_{k=1}^m (|\alpha_k^a| - |\alpha_k^e|) v(k) + \sum_{k=1}^m \left[\sum_{l=1}^{|\alpha_k^a|} h(|\alpha_k^a| - l) - \sum_{l=1}^{|\alpha_k^e|} h(|\alpha_k^e| - l) \right] \quad (\text{A.9})$$

Define $f_{\alpha^a}(k)$, $f_{\alpha^e}(k)$ and $\bar{v}(y)$ as in (A.3) and (A.4). It follows that $0 \leq f_{\alpha^a}(k)$, $f_{\alpha^e}(k) \leq 1$ for $k = 1, 2, \dots, m$. Additionally $\sum_{k=1}^m f_{\alpha^a}(k) = \sum_{k=1}^m f_{\alpha^e}(k) = 1$. Note also that \bar{v} is continuous. It is differentiable over every open interval between integers. It is also non-increasing by Assumption A.2.

Define $F_{\alpha^a}(n) = \sum_{k=1}^n f_{\alpha^a}(k)$ and F_{α^e} in the same way. Since α^a has subgoals of different lengths, we must have $|\alpha_1^a| < |\alpha_m^a|$. Since $|\alpha^a|$ has exactly $|X|$ elements and α_1^a and α_m^a are its smallest and largest subgoals respectively, we must have $|\alpha_1^a| < |X|/m < |\alpha_m^a|$. Let k' denote the smallest k where $|\alpha_k^a| > |X|/m$. We have $f_{\alpha^a}(k) \leq f_{\alpha^e}(k)$ for all $k < k'$, so $F_{\alpha^a}(k) \leq F_{\alpha^e}(k)$ for all $k < k'$. For $k' < k < m$, the identity, $F_{\alpha^a}(k) + \sum_{j=k+1}^m f_{\alpha^a}(j) = F_{\alpha^e}(k) + \sum_{j=k+1}^m f_{\alpha^e}(j) = 1$, implies $F_{\alpha^a}(k) \leq F_{\alpha^e}(k)$ because $\sum_{j=k+1}^m f_{\alpha^a}(j) > \sum_{j=k+1}^m f_{\alpha^e}(j)$. Since $F_{\alpha^a}(m) = F_{\alpha^e}(m)$, we have $F_{\alpha^a} \leq F_{\alpha^e}$. By our Lemma,

$$\begin{aligned} \sum_{k=1}^m \sum_{l=1}^{|\alpha_k^a|} v(|\alpha_k^a|) - \sum_{k=1}^m \sum_{l=1}^{|\alpha_k^e|} v(|\alpha_k^e|) &\leq 0 \\ \sum_{k=1}^m (|\alpha_k^a| - |\alpha_k^e|) v(k) &\leq 0. \end{aligned} \quad (\text{A.10})$$

Define $g_{\alpha^a}(k)$, $g_{\alpha^e}(k)$ and $\bar{h}(y)$ as in (A.6) and (A.7). An identical argument to the proof of Proposition 2 reveals

$$\sum_{k=1}^m \left[\sum_{l=1}^{|\alpha_k^a|} h(|\alpha_k^a| - l) - \sum_{l=1}^{|\alpha_k^e|} h(|\alpha_k^e| - l) \right] \geq 0. \quad (\text{A.11})$$

Thus (A.9) is negative if and only if the magnitude of (A.10) is greater than the magnitude of (A.11), that is, when post-subgoal dominate pre-subgoal factors. Similarly, (A.9) is positive if and only if the magnitude of (A.10) is less than the magnitude of (A.11), that is, when pre-subgoal dominate post-subgoal factors. This leaves (A.9) equal to zero if and only if the magnitudes of the two parts are equal, when there is no dominance between pre- and post-subgoal factors. \square

Corollary. *For a given Δ -set and any i , $T_i(\alpha^d) \geq T_i(\alpha^a), T_i(\alpha^e)$. Provided all the subgoals of α^d are not of the same length, $T_i(\alpha^d) > T_i(\alpha^a)$, if v is non-constant; $T_i(\alpha^d) > T_i(\alpha^e)$ if either v is non-constant or h is strictly increasing.*

Proof. The relation $T_i(\alpha^d) \geq T_i(\alpha^a)$ and $T_i(\alpha^d) > T_i(\alpha^a)$ if not all the subgoals of α_d are of the same length and v is non-constant follow directly from Proposition 1 since α^a and α^d are in the same class of subgoal partitions by definition of Δ -set.

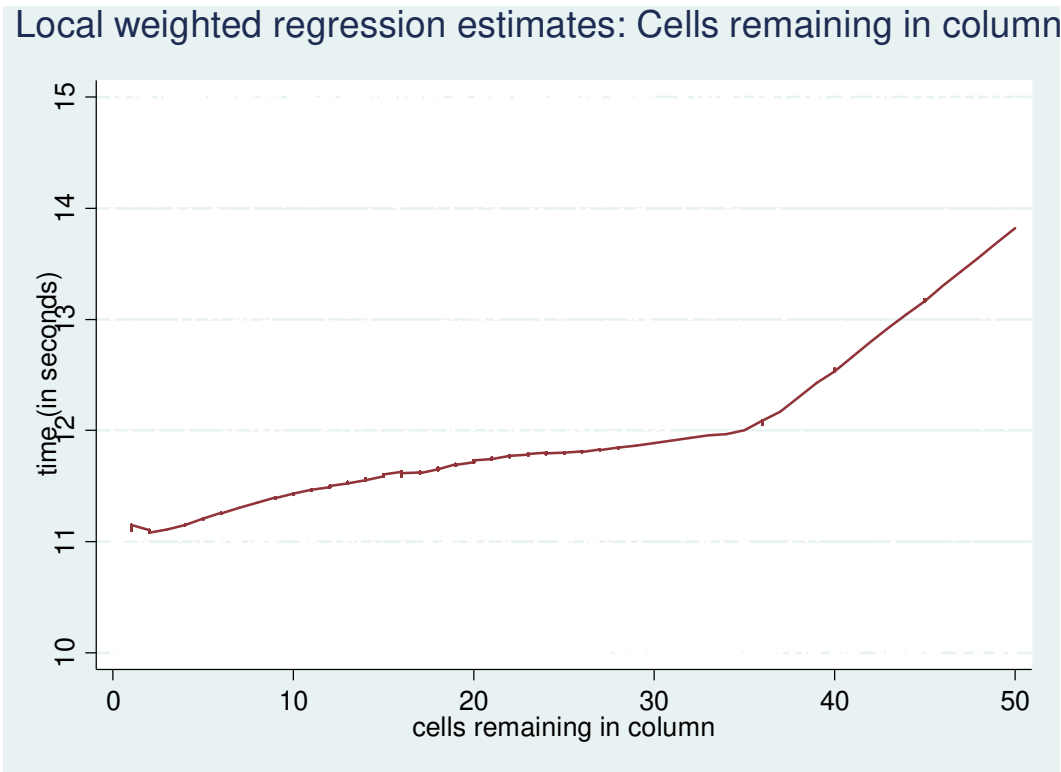
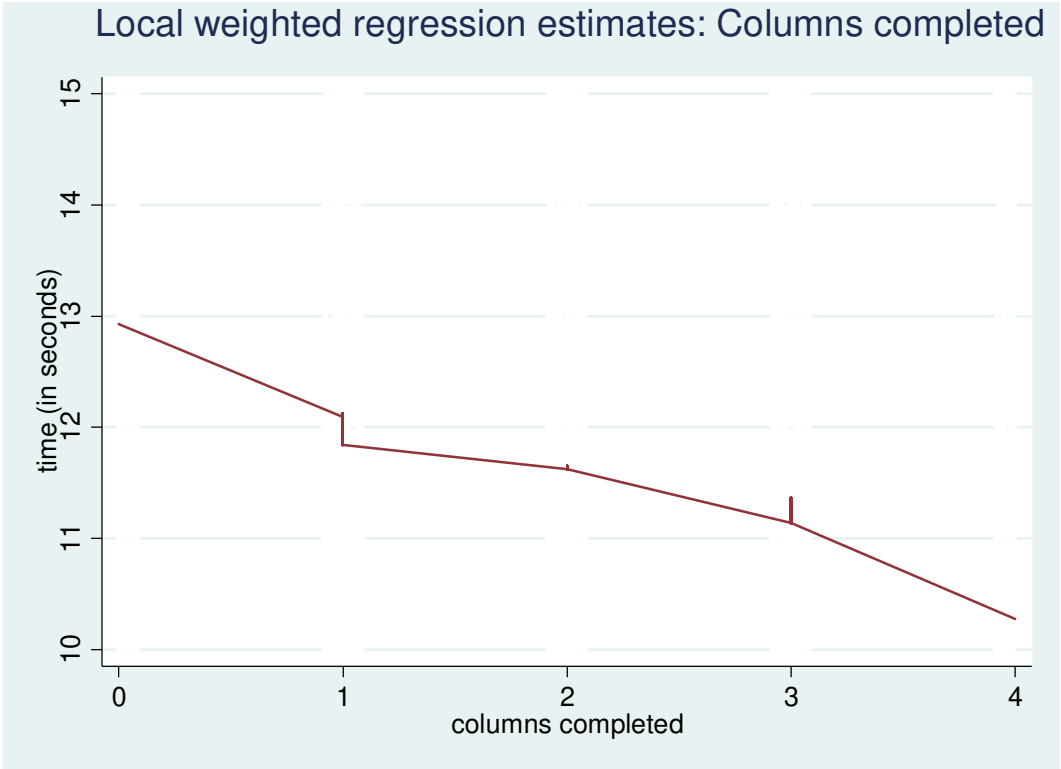
The relation $T_i(\alpha^d) \geq T_i(\alpha^e)$ and $T_i(\alpha^d) > T_i(\alpha^e)$ if not all the subgoals of α_d are of the same length and h is strictly increasing follow directly from Proposition 2 since $|\alpha^d| = |\alpha^e| = m$ by definition of Δ -set.

Now for a given i , $T_i(\alpha^d) - T_i(\alpha^e) =$

$$\sum_{k=1}^m (|\alpha_k^d| - |\alpha_k^e|) v(k) + \sum_{k=1}^m \left[\sum_{l=1}^{|\alpha_k^d|} h(|\alpha_k^d| - l) - \sum_{l=1}^{|\alpha_k^e|} h(|\alpha_k^e| - l) \right].$$

Define $f_{\alpha^e}(k)$, $f_{\alpha^d}(k)$ and $\bar{v}(y)$ as in (A.3) and (A.4). It follows that $0 \leq f_{\alpha^e}(k)$, $f_{\alpha^d}(k) \leq 1$ for $k = 1, 2, \dots, m$. Additionally, $\sum_{k=1}^m f_{\alpha^e}(k) = \sum_{k=1}^m f_{\alpha^d}(k) = 1$. The function \bar{v} is continuous, differentiable over every open interval between integers, and non-increasing by Assumption A.2.

Define $F_{\alpha^e}(n) = \sum_{k=1}^n f_{\alpha^e}(k)$ and F_{α^d} in the same way. Since α^d has subgoals of different lengths, we must have $|\alpha_1^d| > |\alpha_m^d|$. Since α^d has exactly $|X|$ elements and α_1^d and α_m^d are its smallest and largest subgoals respectively, we must have $|\alpha_1^d| > |X|/m > |\alpha_m^d|$. Let k' denote the largest k where $|\alpha_k^d| < |X|/m$. We have $f_{\alpha^e}(k) < f_{\alpha^d}(k)$ for all $k \leq k'$, so $F_{\alpha^e}(k) < F_{\alpha^d}(k)$ for all $k \leq k'$. For $k' < k < m$, the identity, $F_{\alpha^d}(k) + \sum_{j=k+1}^m f_{\alpha^d}(j) = F_{\alpha^e}(k) + \sum_{j=k+1}^m f_{\alpha^e}(j) = 1$, implies $F_{\alpha^d}(k) > F_{\alpha^e}(k)$ because $\sum_{j=k+1}^m f_{\alpha^e}(j) > \sum_{j=k+1}^m f_{\alpha^d}(j)$. Then $F_{\alpha^d} > F_{\alpha^e}$ for $1 \leq k < m$. By our lemma, $\sum_{k=1}^m (|\alpha_k^e| - |\alpha_k^d|) v(k) \leq 0$ with strict inequality if v is non-constant. Since an argument identical to that used in the proof of Proposition 2 shows $\sum_{k=1}^m \left[\sum_{l=1}^{|\alpha_k^d|} h(|\alpha_k^d| - l) - \sum_{l=1}^{|\alpha_k^e|} h(|\alpha_k^e| - l) \right] \geq 0$, we have $T_i(\alpha^d) > T_i(\alpha^e)$ if v is non-constant. \square



Web Appendix, Figures 1a (above) and 1b (below)

Web Appendix Table 1: Comparing first 5 cells in each column to last 5 cells

	Mean (residual)	N	Difference	p (two-sided)
Ascending				
In First Five Cells	-0.2660	775		
In Last Five Cells	-1.3763	730	-1.11	0.0000
Descending				
In First Five Cells	1.6540	635		
In Last Five Cells	0.3443	570	-1.31	0.2307
Equal				
In First Five Cells	0.2144	740		
In Last Five Cells	-0.1965	685	-0.41	0.1307

Notes: Magnitudes are measured as difference from the population average.

Web Appendix Table 2: Comparing first 5 cells in each column to last 5 cells

	Mean (residual)	N	Difference	p (two-sided)
Panel I: Collapsed to First/Last				
Ascending				
In First Five Cells	-0.2660	155		
In Last Five Cells	-1.3763	146	-1.11	0.0011
Descending				
In First Five Cells	1.6705	128		
In Last Five Cells	0.3443	114	-1.33	0.2335
Equal				
In First Five Cells	0.2144	148		
In Last Five Cells	-0.1711	138	-0.39	0.2730
Panel II: Collapsed to Person				
Ascending				
In First Five Cells	-0.2660	31		
In Last Five Cells	-1.2599	31	-0.99	0.0699
Descending				
In First Five Cells	2.3895	29		
In Last Five Cells	0.7737	29	-1.62	0.2948
Equal				
In First Five Cells	0.4238	31		
In Last Five Cells	0.1144	31	-0.31	0.6242
Panel III: Collapsed all Firsts/Lasts Baseline				
In First Five Cells	0.8153	91		
In Last Five Cells	-0.1437	91	-0.96	0.0973

Notes: Panel III groups all firsts and lasts as one observation per person. Magnitudes are measured as difference from the population average for each environment.

Web Appendix Table 3: Effect of baseline treatment interactions with survey data on average cell time

	Barratt	High SSH	Extraversion	Agreeableness	Conscientiousness	Openness	Neuroticism
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
X*ascending	0.1943 (1.2095)	0.3027 (1.1629)	0.1582 (0.1176)	0.1429 (0.1354)	0.1329 (0.1500)	-0.03525 (0.1070)	-0.2034* (0.1217)
X*descending	-1.1639 (1.3108)	-0.6144 (1.3043)	-0.06990 (0.1472)	0.1686 (0.1647)	0.1850 (0.1851)	-0.05391 (0.1341)	-0.2247* (0.1279)
ascending	-1.2418 (0.8183)	-1.5411* (0.8609)	-1.2023* (0.6056)	-1.4210** (0.6874)	-1.2196* (0.6750)	-1.0727* (0.5807)	-2.1063** (0.9536)
descending	0.9077 (0.8651)	0.7421 (0.9751)	0.1653 (0.6668)	-0.09740 (0.7841)	-0.006695 (0.8339)	0.4927 (0.6859)	-0.8077 (1.0452)
X	0.399 (0.9592)	1.0843 (0.9070)	-0.06937 (0.0920)	-0.1215 (0.1194)	-0.1226 (0.1359)	0.1045 (0.0634)	0.1408 (0.1072)
Observations	91	91	91	91	91	91	91

Notes: Outcome is average time to complete one cell in seconds. X is the Barratt Impulsivity measure in column (1), high sensation seeking in Column (2), and columns (3)-(7) are the five factors from the Big Five Inventory. Robust standard errors in parentheses. Omitted treatment is "equal".