

Affect and Cognition as Sources of Motivation:

A New Model and Evidence from the Workplace

Lorenz Goette

Federal Reserve Bank of Boston and CEPR

David Huffman

IZA Bonn

Abstract

In this chapter we propose a model of that incorporates both cognitive and affective aspects of decision-making, and can be used to understand effort allocation when people are working on a long-term project. Consistent with evidence from neuroscience, individuals may experience conflicting cognitive and affective motivations. In particular, the affective system may be influenced by salient sub-goals, or mileposts along the way, and value effort more highly at times when one of these narrowly-defined goals approach. As a result, affect can distort effort decisions relative to a fully cognitive benchmark, which would imply working towards the long-term project at a steady pace. Specifically, our model can predict a *goal gradient*, consistent with experimental evidence showing that animals and humans increase effort as a goal approaches, and predicts an aversion to falling short of a goal, consistent with experimental evidence on *loss aversion*. Also, small windfall gains in terms of progress towards the long-term project may have an impact on an individual's effort profile, by moving the individual closer to one of the narrowly-defined goals. The second part of the chapter tests this latter prediction using data from two bicycle messenger firms, where workers are engaged in the long-term project of accumulating income to pay for future expenses, but may also have a salient, daily earnings goal. At both firms, a windfall gain in the morning has the predicted impact. A lucky messenger works harder than other messengers over the first part of the afternoon, and the difference is increasing, consistent with a goal gradient. Later in the afternoon, a lucky messenger works significantly less hard than the others, consistent with having surpassed a personal earnings goal earlier in the day and having less affective motivation in the form of loss aversion.

1. Introduction

In this chapter, we examine the effort choices individuals make to work towards completion of a long-term project. Many important stages in life involve working on such projects: examples include completing an education, working towards a promotion, working-out to lose weight, or working to generate the necessary income to pay for an important future expense. All of these examples share the property that completion of the project requires effort exerted over a sustained period of time, sometimes many years. Progress towards completion is steady, but each day's effort is only a small step towards completion of the overall project. Until recently, decision research assumed that the primary source of human motivation in these kinds of situations was cognitive. In the purely cognitive framework, motivation to exert effort is modeled as the outcome of a conscious calculation, in which the individual chooses the course of action with the highest net benefit.

By contrast, new evidence points to the importance of affect as a source of motivation.¹ Experiments show that, at every instance, humans (and other animals) tend to evaluate performance on a task relative to a narrowly-defined goals, or mileposts along the way, and experience affect as they make progress, or fail to make progress, towards these more narrowly-defined goals. Narrowly defined goals seem to be pervasive for the types of long-term projects we consider, for instance individuals setting a target on how

¹ This chapter was written for both a psychology and economics audience. Were it is appropriate we define terms that may be unfamiliar to researchers in either discipline. For example, we use the term emotion as it is used in psychology, to refer to a specific feeling state, such as anger, sadness, joy, etc. In all other cases we use the more general term from psychology, affect.

much progress to make on a dissertation per day, how many calories to lose per workout, or how much money to earn per day in a piece rate job.

The affective reaction triggered by progress relative to these narrow goals has an impact on behavior. In particular, affect apparently explains *loss aversion*, a strong preference for not falling short of a reference point or goal, which acts as a psychological incentive to exert effort as long as the individual is below the goal. The tendency for affect to become increasingly intense, as distance from a goal decreases, can explain the so-called “goal gradient effect,” the tendency for humans, monkeys, and other animals to increase effort as a goal draws nearer. This is in contrast to what the standard economic model would predict: broadly speaking, the standard economic model says that exerting effort at a constant pace over every day is optimal when working on a long-term project. An exception is that effort should increase on days when a (random) change in the environment makes the marginal productivity of effort high, and less effort should be exerted on days where effort does not translate into significant progress on the project. But variations in effort over time across or within days, unless they are a response to such external shocks, are not optimal.

This chapter considers the impact of affect on motivation to exert effort on a long-term project. Because the standard model in economics is purely cognitive, the first part of the chapter develops an alternative model that incorporates affect as an additional source of motivation. The key feature of the model is that affect is aroused by performance relative to one or more narrowly-defined goals that must be passed in order to complete the long-term project, e.g., daily page goals as part of working towards a dissertation. This affective motivation can override the priorities assigned by cognitive

decision-making and distort the individual's effort profile on the way to completion of the project. Affect is assumed to respond to the *immediacy* of a goal or reward, increasing in intensity, and creating a stronger motivation to exert effort, as one of the narrowly-defined goal draws near. We formalize this tension between affect and cognition in similar way to Loewenstein and O'Donoghue (2005), by assuming a two-part objective function for the individual, where one part corresponds to the preferences of the forward-looking, cognitive self, and the other to the more-myopic process that drives affective impulses.

We show that our model generates a psychological incentive to not fall short of a goal, consistent with experimental evidence on loss aversion, and predicts an increasing effort profile leading up to a goal, consistent with experimental evidence on the goal gradient effect. The model also predicts that a temporary shock to productivity, e.g., a day on which it is particularly easy for individuals to make progress on their long-term project, may lead to lower total effort on that day, because it causes the individuals to reach their daily goals more quickly and thus removes some of the motivation arising from affect earlier in the day. This finding is at odds with a central prediction of the standard economic model, that individuals should work harder when a shock makes their productivity temporarily high. It is consistent, however, with a body of anecdotal evidence: students working particularly long hours on days when they have not been very productive, in order not to fall short of a page-per-day target; individuals extending their workout time on days when they feel lethargic, because by the end of their usual workout time they are still below a calories-per-workout goal; piece-rate workers knocking-off

work early on a day when they earned more than usual and were able to surpass a daily income target particularly quickly.

In our view the best-developed source of evidence on these mechanisms is the literature examining day-to-day effort choices of workers paid on piece rates. This recent literature focuses on types of workers that are free to vary effort over the workday, such as cab drivers, bicycle messengers, and manual workers. The key stylized fact from this literature is that a worker's total daily effort is typically unchanged, or even decreases, on days when the wage is temporarily high (for a review see Goette, Huffman, and Fehr, 2004).

The second part of the chapter presents new empirical evidence on the relevance of affect for motivation, using data from a real work setting where workers face strong financial incentives. Our data come from two bicycle messenger firms, and allow us to observe the within-day effort profiles of individual messengers. Bicycle messengers are attractive subjects for study because they have relative freedom to choose their effort. It is also important that luck plays a significant role in determining their daily earnings: messengers are paid a piece rate, and can earn substantially more or less than expected on a given day simply because they were lucky and obtained an attractive assignment.

Our strategy is to see how good luck or bad luck (windfall gains or losses) early in the day affect effort profiles later in the day. The standard model predicts that within-day windfall gains should have no impact on effort, because they are trivial with respect to the long-term project of accumulating income. By contrast, the affect-based model predicts that windfall gains in the morning can have a significant impact on the effort profile over the afternoon. A lucky morning can position a messenger quite close to the narrowly

defined daily goal by the first hours of the afternoon, with the result that the goal gradient takes effect earlier, and messenger works harder, compared to other messengers. Later in the afternoon, when other messengers are getting close to their goals, the lucky messenger has already achieved the goal and thus works less hard. In fact, we find exactly this pattern, at both firms: afternoon effort is positively correlated with a windfall gain in the morning over the first few hours of the afternoon, but negatively correlated with a windfall gain in the morning over the final hours of the day. We also conducted a complementary survey with bicycle messengers, in which we asked directly about the importance of a daily earnings goal for motivation to exert effort, and find additional evidence supporting the alternative model of labor supply.

These findings contribute to the recent empirical literature on labor supply and loss aversion, which builds on the finding, already mentioned, that total daily effort sometimes decreases in response to a wage increase. The seminal paper in this literature, Camerer *et al.* (1997), studied New York City cab drivers and argued that the tendency for cabbies to work short hours on high wage days reflects loss aversion around a daily income target. More recently, Fehr and Goette (2007) conducted a field experiment in which bicycle messengers were given a higher wage for one month, and found that messengers decreased effort during shifts in this month. The decrease was strongest for messengers who were loss averse, as measured by a lottery experiment. This chapter extends the income-targeting hypothesis by emphasizing the affective underpinnings of loss aversion, and by building a dynamic model of progress towards a daily goal that incorporates another aspect of affective evaluation, namely immediacy. The model can predict a decrease in daily effort due to an increase in the wage (productivity), consistent

with previous findings, but also generates a new prediction linking income targeting to affect, i.e. the goal gradient, which is testable using our data on within-day effort profiles. Importantly, this strategy avoids some of the concerns raised about interpretation of the findings in Camerer *et al.* (1997), and provides new support for the income-targeting hypothesis.²

The broader theme of this volume is whether affect leads to better or worse decisions by individuals. We discuss this question in the conclusion of the chapter, after presenting our empirical results. The chapter is organized as follows. Section 2 describes the standard economic model of labor supply, and proposes an alternative model incorporating affect. Section 3 describes the data and empirical design. Section 4 presents the empirical results. Section 5 concludes.

2.1 Working on Long-Term Projects: The Roles of Cognition and Affect

2.1.1 The Cognitive Model of Working on a Long-Term Project

The standard economic model captures the deliberative side of human decision-making, and can be applied to the case of working on a long-term project. Examples of long-term projects include working towards a dissertation, studying to earn useful qualifications, putting in effort on the job in order to generate enough income to meet major future expenses, or working towards a promotion. All these examples have in common that it takes effort over a prolonged period of time to complete the project, and that there is

² E.g. in Camerer *et al.* and other cab driver studies it is not clear whether wage variation is exogenous to effort choices. For a discussion of this point see Fehr and Goette (2007) and Farber (2005).

some threshold amount necessary to achieve completion. Progress towards the long-term project is a function of effort, but also random occurrences that are beyond the individual's control. Our aim here is to examine how effort put into the project will vary over short time horizons after a random shock occurs. In particular, we want to examine how sensations of progress, or lagging behind, narrowly-defined goals affects effort on the long-term project.

Formally, in order to complete the long-term project, cumulative effort has to exceed a threshold Q :

$$\sum_{t=1, \dots, T} w_t (e_{0t} + e_{1t} + e_{2t}) + z_t \geq Q \quad (1)$$

The term e_{0t} is effort “in the morning” of date t , while e_{1t} and e_{2t} is effort put into the project in the early and late afternoon of date t . Not all days are equally productive: we model this with the factor q_t which affects the rate at which effort increases output towards the goal. There is also an element of luck in progress towards the goal, reflected in the term z_t , which is out of control of the individual. We also assume that effort exerted in each episode is costly. In particular, we assume that effort becomes increasingly painful as effort increases. Formally, in each work episode effort costs are given by a convex function of effort $c(e)$, with the property that the marginal costs of effort are increasing.

It can easily be shown that the optimal effort level in hour t is the amount of effort such that the extra benefit from exerting another unit of effort is just offset by the extra cost of that unit. Formally, the optimal level solves the following first order condition:

$$c'(e_{mt}) = \lambda w_t \quad (2)$$

Where $c'()$ is the cost of one additional unit of effort, and λw_t is the increase in utility from exerting an additional unit of effort. The term λ reflects the how much the individual's utility is increased by a one-unit increase in output towards the long-term threshold Q , while w_t is the temporary productivity with which effort is translated into progress towards Q on day t .

There are two important implications from (2). The first is that an increase in w_t should lead to an increase in effort, limited by how quickly effort costs increase. Intuitively, in order to maximize utility the individual should take advantage of temporarily high productivity and put in extra effort, because progress per unit of effort is higher than usual. The second important implication is that windfall gains in progress towards the goal, z_t in equation (1), should not affect labor supply to a first approximation. These windfalls do affect the overall distance to completion, but for a long-term project the change is minimal.³

Our empirical analysis in the second portion of the chapter considers effort choices, i.e., labor supply, of piece rate workers. In this labor supply setting, it is natural to interpret w_t as the piece rate, which determines progress per unit of effort towards a long-term project of earning an income amount Q , sufficient to meet future expenses. In

³ Intuitively, the insensitivity of λ to small z_t follows from the assumption that the individual plans over the entire time span needed to achieve Q . With this time horizon in mind, the individual uses any windfall gain in progress to reduce work effort by a small amount in every future period. Given that a lucky day leads to a change in z_t that is very small relative to Q , the resulting change in effort in any single future period will be essentially zero.

this context, a windfall gain z_t could be a generous tip, or some other lucky burst of productivity on day t . The only channel through which this windfall could influence effort would be through λ . However, if the windfall z_t is small relative to the needed income Q , then λ is constant with respect to small windfall gains. We test this prediction later in the chapter, in our empirical analysis.

2.1.2 Incorporating Affect

Evidence on the role of affect and cognition in decision-making

Recent research in neuroscience provides groundwork for understanding the roles of cognition and affect in determining individual motivation. A prominent model in neuroscience is that cognition and affect are governed by distinct neural systems in the brain (for an overview see Cohen, 2005). The affective system, closely related to what Satpute and Lieberman (2004) define as the reflexive system, is thought to include older brain structures such as the basal ganglia, the amygdala, ventromedial prefrontal cortex, and parts of anterior cingulate cortex. The cognitive system, or reflective system in Satpute and Lieberman (2004), includes lateral prefrontal cortex, ventral parts of anterior cingulate cortex, parts of the temporal lobes, as well as posterior parietal cortex.

An important implication of the dual-process structure of the brain is the possibility for conflicting motivations. Conflict can occur because the affective system has a relatively “conservative” set of pre-programmed priorities, which may ignore some of the broader, long-term considerations that inform cognitive decision-making.

One example of the affective system’s conservatism is a tendency to prioritize immediate rewards and threats over longer-term considerations. A famous series of

studies in psychology demonstrates the impact of immediacy on impulsive behavior, by showing that subjects are more likely to choose a small, immediate reward over a larger, delayed reward if the immediate reward is visible at the time of the decision (Mischel *et al.*, 1972; Mischel *et al.*, 1989; Mischel *et al.*, 2003) More recently, McClure *et al.* (2005) find evidence suggesting that the cognitive system of the brain is involved in making intertemporal tradeoffs in general, but that the affective system is activated only when the tradeoff involves an immediate reward. The relative strength of activation of these two systems predicts whether the individual chooses an immediate reward or waits for the larger, delayed reward.

The affective system is also conservative when it comes to the possibility of losses. Choice experiments reveal that many people exhibit reference-dependent valuation, defining outcomes in terms of gains or losses relative to a reference level. In these evaluations, people tend to be *loss averse*, disliking losses more than they like gains of the same amount (for a review of evidence on reference dependence see Tversky and Kahneman, 2000). Loss aversion prevents an individual gambling on options involving very high risk, a pattern that may be useful to avoid most harmful outcomes. Several studies show a clear involvement of brain networks associated with affective (reflexive) system when individuals make loss-averse choices. Tom *et al.* (2007) find that loss-averse behavior correlates with brain activity in VMPFC and ventral striatum. Shiv *et al.* (2005) conduct a choice experiment involving real-stakes lotteries, in which the subjects include individuals with damage to the VMPFC. Shiv *et al.* find that normal subjects display loss aversion, but the brain-damaged patients do not. This points to VMPFC as a brain region necessary for behavior to exhibit loss aversion. More indirectly, Chen *et al.*

(2005) provide evidence that loss aversion is seated in the structures of the brain, which humans and monkeys have in common, by showing that even capuchin monkeys exhibit loss aversion with respect to gambles.

Affect and task motivation

A number of studies provide direct evidence on the importance of affect for motivating task effort. Consistent with the myopic, reference-dependent character of the affective system, affect is found to play a role mainly when an individual has a goal or reference point in mind, and when the individual is close to achieving that goal. The resulting effort profile involves higher overall effort below a goal, with an increasing “goal gradient” in effort up until the point when the goal is achieved.

A study by Heath, Larrick and Wu (1999) finds evidence that goals act as reference points, and that affect provides a source of motivation to achieve goals, in a way that is consistent with loss aversion and the goal gradient. Heath, Larrick, and Wu posed subjects with the following hypothetical scenario:

Sally and Trish both follow workout plans that usually involve doing 25 sit-ups. One day, Sally sets a goal of performing 31 sit-ups. She finds herself very tired after performing 35 sit-ups and stops. Trish sets a goal of performing 39 sit-ups. She finds herself very tired after performing 35 sit-ups and stops. Who is experiencing more emotion?

Most subjects indicate that Trish, who is below her goal, is experiencing more emotion than Sally who is above her goal by the same amount [Trish, 71%; Sally, 29%; N=48]. This is consistent with the goal acting as a reference point and triggering the type of affective response, discussed above, that appears to play a role in explaining loss aversion. In another question, Heath, Larrick and Wu describe a similar situation, but ask

who will exert more effort to do one more sit-up. Again, the question is careful to hold previous effort constant. Most subjects indicate that the individual below the goal will exert more effort than the individual who has surpassed the goal, consistent with loss aversion serving as a source of motivation [Above goal, 82%; Below goal, 18%; N=73]. Finally, Heath, Larrick and Wu ask a question in which two individuals have completed the same number of sit-ups, and are both below their goal, but have different goals. Consistent with the goal gradient, and an increasing role for affect as a goal draws near, subjects indicate that the individual with the closer goal will work harder to perform one additional sit-up [Close to goal, 86%; Far from goal, 14%; N=74].

The first behavioral evidence of a goal gradient was observed in studies using animals. The seminal empirical study on the goal gradient was Hull (1934), which showed that rats run progressively faster in a straight runway as they approach a food reward. Other animal studies followed, documenting a similar pattern in effort towards a goal (for a review see Heilizer, 1977).

More recently, some animal studies have found evidence, at a neurological level, suggesting that the affective system plays a role in generating the goal gradient in effort. Shidara, Aigner, and Richmond (1998) and Shidara and Richmond (2002) monitored the brain activity of monkeys as they exerted effort to reach a reward, and found selective response in the ventral striatum and anterior cingulate, respectively, as visual cues signaled increasing proximity to the reward (distance to the reward was varied randomly over time, so monkeys had to rely on cues to infer current proximity). These structures are believed to be part of a loop between reward expectancy, affective response, and effort. At the same time that the monkeys exhibited increasing activation in these parts of

the affective system, they also exhibited a goal gradient, increasing effort and making fewer mistakes on the task as distance to the goal decreased.

See, Heath, and Fox (2003) provides evidence of similar pattern of behavior in humans, in a study using college athletes. In this study, a goal was marked on a 400-meter track, and a subject was positioned at one of two distances from the goal. The subject was then instructed to start running at a gradual pace, until hearing a loud noise generated by the experimenters, which could happen at any time. The subject was told that the noise signaled the beginning of a 10 second period, during which they should try as hard as possible to reach the goal line. The treatment variable was the distance remaining to the goal when the noise was produced. Importantly, both groups of subjects heard the noise at a point when the goal was clearly unattainable in 10 seconds time; distances to the goal were clearly marked on the track, and all subjects were aware of relevant world-record times indicating that the goal was impossible. The main finding of the study is that subjects who heard the noise at a closer distance to the goal ran harder than subjects who heard the noise when they were relatively far from the goal, consistent with the goal gradient effect. Notably, subjects were put in a position where they had to make decisions very quickly, and were thus especially likely to be motivated by the fast-acting affective system of the brain.

Kivetz, Urminsky, and Zheng (forthcoming) also find behavioral evidence of a goal gradient among humans, but in the domain of consumer choice. In one experiment, people were offered cards allowing them to receive a free coffee after they had purchased nine previous coffees. Consistent with the goal gradient, participants increased the frequency of coffee purchases as distance from the reward decreased. A similar pattern

was observed in an online experiment in which participants received a reward after rating a certain number of songs.

A New Model of Motivation to Work on a Long-Term Project

In the remainder of this section we develop a model of behavior that nests the traditional, cognitive model of working on a long-term project but also includes affect as another source of motivation. Building on the evidence from psychology and neuroscience surveyed above, we design the model to allow for conflict between cognitive decision-making and affective impulses, and we formalize the affective system in a way that captures the key properties of affective evaluation. We also adopt the terminology of labor supply in the workplace, in preparation for the empirical test in the next section, but the model can still be interpreted as applying to long-term projects more generally.

In the spirit of Loewenstein and O'Donoghue (2005) and other “dual-process” models in economics (Thaler and Shefrin, 1981; 1988; Bernheim and Rangel, 2003; 2004; Benhabib and Bisin, 2004; Fudenberg and Levine, 2004), we assume a two-part objective function for the individual. The first part describes the preferences that inform the individual's cognitive decision-making. Exactly as in the standard model of labor supply in economics, this portion of the objective function values progress towards the long-term project (maximizing lifetime income) linearly over the course of work period t . More formally, net utility in period t , from a cognitive perspective, is given by:

$$U_t = w_t e_t + z_t - c(e_t) \tag{3}$$

Where the utility from an additional unit of progress towards income threshold Q , λ , is normalized to 1, w_t is the wage in period t , z_t is income from previous periods that is

unrelated to current period effort, and $c()$ is a convex function capturing the cost of effort in utility terms. We denote the optimal level of effort from the perspective of the cognitive system as $e_t^c = \operatorname{argmax} U_t$.

The second part of the worker's objective function corresponds to the preferences of the affective system. Consistent with reference-dependence, the affective system's valuation of income over the day is assumed to vary with distance from a daily goal, or income target, denoted r . Importantly, this valuation is assumed to be nonlinear, in a way that reflects increasing motivation as distance to the goal decreases, and dissipation of motivation once earnings have surpassed the narrowly-defined (daily) goal. We formalize the net benefits of effort in period t , to the affective system, as:

$$v(w_t e_t + z_t - r) - c(e_t) \tag{4}$$

The function $v()$ captures the affective system's valuation of progress on the project. We assume that $v'()$, the additional value to the affective system of an additional unit of income, is increasing as total daily output approaches r from below, consistent with increasing motivation. Once total earnings have surpassed r , however, $v'()$ is assumed to decrease with further output, reflecting a dissipation of motivation. Furthermore, we assume that $v'(-x) > v'(x)$ for any $x > r$, i.e. the affective value of an additional dollar is always greater when the individual is below the goal, consistent with loss aversion.⁴ We

⁴ This final assumption corresponds to the notion of strong loss aversion (Neilson, 2002), and implies a kink in $v()$ at zero. Given these assumptions $v()$ is equivalent to the "Kahneman-Tversky" value function, proposed by Kahneman and Tversky (1979) as a description of reference-dependent evaluation of outcomes. In this sense our model is similar to Wu, Heath, and Larrick (2002), who propose a dynamic, value-function based

denote the optimal level of effort from the perspective of the affective system as $e_t^A = \arg \max V_t$.

Following Loewenstein and O'Donoghue (2005), we combine the cognitive and affective components into a single objective function, and assume that the worker tries to achieve the cognitive optimum, e^C , in each work period, subject to willpower costs involved in moving effort away from the affective optimum, e^A . Willpower costs are denoted h and are assumed to increase linearly in “distance” between the chosen effort level, e^* , and the effort level preferred by the affective system. We also assume that the worker does not take into account the impact of current effort on willpower costs in future periods.⁵

Having defined the objective function, we can write down the worker's decision problem. To fix ideas, and in line with our empirical analysis in the next section, we will focus on a worker's effort decisions over the afternoon, conditional on morning earnings. For simplicity we assume that the afternoon has only two periods. In this case the model of working towards a goal. An important difference is that they assume the individual is completely myopic. We assume that the affective system is myopic, but allow for forward-looking decision making on the part of the cognitive system.

⁵This does not mean that the individual is “naïve,” ignoring the impact of current effort on the decisions of future selves; the individual still has a strategic interest in encouraging future selves to adhere to current-period preferences. Rather, the assumption is that the individual does not incorporate the willpower costs of future selves directly into the current period utility function, and thus would, if possible, force future selves to exert maximum willpower, without regard for discomfort experienced by future selves.

worker's decision problems, in the first and second periods of the afternoon, can be written:

$$\text{Max}_{e_1} Q_t = w_1 e_1 + w_2 e_2 - c(e_1) - c(e_2) - \quad (5)$$

$$-h[v(w_1 e_1^A + z_1 - r) - c(e_1^A) - (v(w_1 e_1 + z_1 - r) - c(e_1))]$$

$$\text{Max}_{e_2} Q_t = w_2 e_2 - c(e_2) - \quad (6)$$

$$-h[v(w_1 e_1^A + w_2 e_2^A + z_2 - r) - c(e_2^A) - (v(w_1 e_1 + w_2 e_2 + z_2 - r) - c(e_2))]$$

Willpower costs are captured by the terms in brackets, which express the difference between the affective system's objective function, evaluated at the affective optimum, e^A , and the affective system's objective function evaluated at the worker's chosen effort level. Willpower costs are thus equal to zero if the worker complies with the wishes of the affective system, and increase linearly in deviations from e^A .

The optimal effort levels in period 2 and period 1 are then given by the following first order conditions:

$$c'(e_1) = w \frac{1 + hv'(w_1 e_1 + z_1 - r) + \left[\frac{h(1 - v'(w_1 e_1 + w_2 \tilde{e}_2 + z_2 - r))}{1 + h} \frac{\partial \tilde{e}_2}{\partial e_1} \right]}{1 + h} \quad (7)$$

$$c'(e_2) = w \frac{1 + hv'(w_1 e_1 + w_2 e_2 + z_2 - r)}{1 + h} \quad (8)$$

Where \tilde{e}_2 is the effort that the period-1 self expects to exert in period 2. A first observation is that affect can lead to either lower or higher effort levels, compared to effort levels predicted by the standard model. One determining factor is quite intuitive, and can be seen by comparing (8) to the condition for optimal effort in the standard, cognitive model. According to (8), effort in period 2 is higher than in a purely cognitive

model if the value that the affective system places on an additional dollar of income, $v'()$, is greater than 1, which is the value the cognitive system places on an additional dollar (recall that λ was assumed to be equal to 1). Similarly, if the affective system cares less about income than the cognitive system, i.e., $v'() < 1$, effort in period 2 is lower than in a purely cognitive model.

The condition for effort in period 1 is more complicated. The term in brackets in (7) arises because the individual is assumed to be forward-looking and “sophisticated,” i.e. to take into account the impact of current effort choices on behavior in period 2. Effort in period 1 has an impact on effort in period 2 by changing distance from the goal, and thus the affective system’s valuation of income in the second period. Whether effort in period 1 is higher or lower than effort in the standard model thus depends on two factors: whether the affective system’s valuation of income in period 1 is more or less than 1, and whether the additional sophistication motives captured by the terms in brackets tend to increase or decrease effort in period 1.

Although in general the impact of affect on effort is ambiguous, we now turn to two specific examples in which the affective system in the model leads to a goal gradient, consistent with experiments on task effort. We also show that in each case a windfall gain in the morning, reflected in an increase in z_t , leads to greater effort in period 1 and lower effort in period 2, a prediction that we will test in the empirical analysis later on. Finally, we explain how an increase in the daily wage could lead to a decrease in total daily effort.

As a first example, suppose the individual is below the goal in both periods of the afternoon, reaching the target only at the very end of the day. Furthermore, assume that the individual is naïve, i.e. does not take into account the impact of current effort on

future affective evaluations, so that the bracketed terms in (7) disappear. In this case the model clearly predicts a goal gradient, i.e., $e_1 < e_2$, because the individual is closer to the goal, and $v'()$ is larger, in period 2. Now suppose that the individual experiences a windfall gain in the morning, such that the individual is above the goal in period 2. Period 1 effort must be higher than before, because the individual is now relatively closer to the goal in period 1. In period 2, effort is lower than before, because the individual is beyond the goal and the affective valuation of income is lower. Thus the model predicts a positive response of effort early in the afternoon, and a negative response later in the afternoon, after a windfall gain in the morning.

The model makes the same prediction in the next example, in which the individual is now assumed to be sophisticated, provided that the affective system places a relatively large value on income, i.e. $v'() > I$ in both periods. In this case, sophistication effects reinforce the goal gradient. Intuitively, $v'() > I$ implies that the affective system cares “too much” about income in the second period. This gives the first period self a motive to reduce effort in period 1, in order to increase distance from the goal in period 2 and thus reduce the affective system’s valuation of income in the second period. Formally, this result arises because the sign of the product in the brackets in (7) is negative, leading to even lower effort in period 1 compared to period 2. To see this, note that the derivative of \tilde{e}_2 with respect to e_1 is positive, because effort in period 1 moves the individual closer to the goal in period 2, which increases \tilde{e}_2 . Given $v'() > I$, the sign of the product is unambiguously negative. Turning to the case where a windfall gain in the morning causes the individual to be above the goal in period 2, sophistication effects reinforce the tendency for effort to increase in period 1 and decrease in period 2. To see

this note that the product in brackets is now positive, because the derivative of \tilde{e}_2 with respect to e_1 is positive: an increase in e_1 places the individual farther beyond the goal in period 2 and thus leads to a lower \tilde{e}_2 .

A final noteworthy feature of the model is the predicted response to a wage increase. In line with empirical evidence that workers sometimes reduce total daily effort on high wage days, the model can predict a decrease in total daily effort if the wage goes up. To see this, suppose that on a low wage day the worker is below the goal for the whole day. On a high wage day, by contrast, it is easier to reach the goal, say by the second period in the afternoon. As discussed above, switching from being above the goal to being below the goal in period 2 can decrease effort in period 2, because the affective system no longer places a high value on income once the goal is achieved. Although a wage increase tends to encourage higher effort, through the channel of purely financial incentives considered by the cognitive system, and due to the goal gradient in earlier periods of the day, a strong drop in period 2 effort could result in a net drop in total daily effort. The model predicts that the drop in effort is more likely to dominate if workers are allowed to quit early, i.e. reduce effort in period 2 all the way to zero, consistent with findings in the empirical literature. E.g. Fehr and Goette (2007) find that a wage increase causes a relatively small decrease in daily effort at a Swiss bicycle messenger firm, where messengers are able to reduce effort, but are not allowed to quit entirely, before the end of their daily shift. Camerer *et al.* (1997) find a larger decrease in effort among cab drivers, potentially reflecting the greater freedom of cab drivers to quit early.

3. Data Description and Empirical Design

3.1 Data

In order to test the relevance of affect for labor supply choices in a real work setting, we analyze data from two bicycle-messenger firms operating in the same city, which we will call Firm A and Firm B. Bicycle messenger firms offer same-day, or same-hour delivery of packages, in urban areas where traffic-congested streets make a bicycle the fastest method of delivery. At the firms we study, messengers are paid a simple piece rate, which is a fixed fraction of the price of each delivery (50 percent). Delivery prices vary based on the distance the messenger must carry the delivery, how quickly the customer needs the delivery, and the weight of the package.

Bicycle messengers are attractive subjects for the study motivation and effort, because they have substantial discretion over how hard they work, and when, during a workday. Deliveries are announced over the airwaves by a dispatcher, and are heard by all of the company's messengers working that day. Messengers have several ways to vary effort in this setting: they can work hard to finish deliveries quickly, and lobby the dispatcher for more deliveries, or they can make deliveries slowly, and respond slowly to the dispatcher's calls on the radio.

We use the electronic delivery records of Firms A and B to study the effort decisions of individual messengers. These records span several years for each firm, and include all deliveries made by all workers. Crucially, the records include the date, and time of day of each delivery made by a messenger, as well as the price of the delivery. With this information we are able to see the effort profile over the day of each messenger, and study the impact of windfall gains in the morning on effort profiles in the afternoon.

We also conducted a survey with messengers in the same city.⁶ A total of 119 messengers returned completed surveys, giving us a response rate of roughly 60 percent. The survey was administered in two ways: (1) we contacted messenger firms, and arranged to leave the survey in the mailboxes of the messengers at these firms; (2) during the working day, we handed-out surveys to messengers waiting for deliveries at one of several well-known waiting spots. Messengers were paid for completing the survey, and had a deadline of four weeks to return the survey. Most messengers returned the survey within a few days.

3.2 Descriptive Statistics

We begin our analysis with some simple descriptive statistics. These give a sense for the typical working day experienced by a bicycle messenger, and point to the importance of luck for determining a messenger's daily earnings.

Table 1 describes the length of the working day for a bicycle messenger, in terms of total hours on the job. At both firms, the majority of messengers are on the job for 10 hours, but there appears to be some margin for quitting early or working late: roughly 20 percent work only 9 hours and 20 percent work 11 hours or more. Figure 1 shows the distributions of quitting and starting times at the two firms. The majority of messengers start work between 8:00 and 9:00 am, and 80 percent have started by 10:00 am. In the afternoon, only about 5 percent of messengers have quit by 4:00. Roughly 10 percent quit

⁶ We obtained permission to conduct the survey from the Committee for the Protection of Human Subjects at the University of California, Berkeley.

between 4:00 and 5:00, 40 percent quit between 5:00 and 6:00, and 35 percent quit between 6:00 and 7:00.

Figure 2 shows the distributions of daily earnings for messengers at Firm A and Firm B. Two features of these distributions are noteworthy. First, they are quite similar across firms. Second, daily earnings are highly variable. The standard deviation of daily earnings is \$46.27 at Firm A and \$50.29 at Firm B. Morning earnings, not shown, are also similarly variable, with a standard deviation of roughly \$30.00 at both firms.

There are several possible sources of the variation in earnings for a messenger. In this chapter we are particularly interested in the variation in morning earnings that represents windfall gains, or luck. However, some of the variation in earnings is certainly due to day-to-day fluctuations in demand for messenger services, or differences in messenger characteristics. Therefore, to assess the importance of windfall gains for determining a messenger's earnings, we must first remove the variation due to day and messenger effects. Table 2 shows an analysis of variance for morning earnings. The adjusted R-squared statistics indicate that day and messenger effects explain a significant portion of the variation in morning earnings at both firms. However, consistent with an important role for luck in determining morning earnings, there remains substantial unexplained variation. This variation is economically meaningful to messengers, as shown by the fact that the standard deviation of unexplained variance is equivalent to roughly 30 percent of a messenger's average morning earnings.

There are two important sources of randomness in daily earnings for a bicycle messengers. First, earnings vary with the characteristics of a delivery – the service type, and the pick-up and drop-off zones of the delivery – which are not necessarily correlated

with the effort required to make the delivery. For example, two deliveries may involve the same effort, but because one happens to cross the border of a pricing zone in the city, it may generate significantly higher earnings. Messengers also talk about the importance of luck in generating a collection of deliveries that “line up,” allowing the messenger to deliver all packages along a roughly linear path rather than having to make significant detours for each one. The second important source of randomness comes from the fact that if one messenger gets a delivery, due to fortunate timing in answering the dispatcher’s call, this prevents another messenger from getting the delivery.

3.3. Empirical Design

Our empirical strategy is to test for an impact of windfall gains in the morning on effort in the afternoon. In the standard model, within-day windfall gains should have no impact on effort, because they are trivial relative to lifetime and thus cannot change the marginal valuation of income. On the other hand, if workers attach affective significance to the level of their daily earnings, windfall gains could have an impact on effort. The alternative model formulated in this chapter makes a distinct prediction regarding the impact of a windfall gain in the morning: a worker who had a lucky morning is predicted to work harder than other messengers at the beginning of the afternoon, because they are relatively closer to reaching their goal, and then work less hard than the others towards the end of the day, because they have already surpassed their goal.

Our analysis focuses on the relationship between windfall gains in the morning and afternoon effort. Although we could measure windfall gains in terms of earnings, we will use revenues, which are a simple function of earnings ($\text{earnings}/0.50$) have the

advantage that they yield a direct interpretation in terms of benefits for the firm. We calculate a messenger's morning revenues on a particular day by summing the value of all deliveries a messenger completed between the beginning of work and lunchtime.

We measure effort in the afternoon as follows: we follow each messenger working on a particular afternoon for 6 hours, starting at 1:00 pm (6 is the maximum number of hours a messenger works in the afternoon at both firms), and use hourly revenues as an indicator of effort. This creates six measurements of hourly effort for a messenger working on a particular afternoon. If a messenger had zero revenues during an hour, we set effort to zero in that episode. This measure of work effort is the broadest possible, and is precisely as standard economic theory suggests it should be. It captures (i) how hard a messenger is working, (ii) whether he is taking breaks during the day, and (iii) when the messenger quits for the day (after the messenger quits, we set effort to zero for the remaining hours in the workday).

We then estimate equations of the form:

$$e_{ikt} = \gamma^1 Morning_{ikt}^1 + \gamma^2 Morning_{ikt}^2 + \dots + \gamma^6 Morning_{ikt}^6 + \beta x_{it} + a_i + d_t + \varepsilon_{ikt} \quad (9)$$

Where e_{ikt} is effort of messenger i at hour k on date t . Our coefficients of interest are the γ^k coefficients: the variable $Morning^k$ is the product of morning revenues for the individual and a dummy variable equal to one if it is the k^{th} hour of the afternoon. We want the γ^k coefficients to reflect the impact of windfall gains on effort in work hour k . For the coefficients to have this interpretation, we need to control for factors that determine variation in morning revenues besides luck.

The vector x consists of time-varying, individual control variables. These include starting hour on day t , days of experience at the firm, as well as dummy variables equal to

1 if the messenger worked the day before or the day after date t , to control for fatigue spillovers between days. We also include a messenger fixed effect, a_i , to control for time-invariant individual characteristics, such as ability, and a fixed effect, d_{ht} , which we estimate separately for each day at each firm to control for firm-specific, day-specific shocks, such as weather.

With these controls in place, γ^k indicates by how much the messenger changed effort in work hour k in response to an increase in windfall gains in the morning. The model incorporating affect predicts positive values for γ^k early in the afternoon and potentially negative values for γ^k later in the day. The prediction of the standard model is that γ^k should be zero for all hours.

One caveat is that we might not eliminate all factors driving morning revenues besides luck. If a portion of the variation in morning earnings is still positively correlated with effort in the morning, and morning effort causes fatigue and makes it harder to work in the afternoon, then the standard model could predict negative γ^k 's in the afternoon.⁷ This is unlikely given our controls, however, and given that messengers typically take a lunch break and have the opportunity to rest, minimizing the relevance of fatigue effects from the morning. Also, this channel should not lead to the reversal in correlation predicted by the alternative model; if workers with high morning earnings are fatigued they might work less hard in the afternoon, but the standard model does not predict a goal

⁷ Fatigue spillovers could be incorporated by making the slope of the cost function for effort in period t an increasing function of effort exerted in previous periods, as we do in Goette and Huffman (2005).

gradient effect, i.e. γk^2 's that are *increasing* over the first portion of the afternoon. Thus a goal gradient is an indication that affect, and not fatigue, explains the response to changes in morning earnings.

We estimated our baseline regression equation using OLS. An important issue is how one should calculate the standard errors of the estimated coefficients. Given the hourly frequency of our measures, there are various ways in which ε_{it} , the error term, departs from the i.i.d. assumption of OLS. First, the way we construct our measure of labor supply makes the error term inherently heteroskedastic.⁸ We correct for this by estimating robust standard errors. Second, there are two potential sources of correlation between the error terms. Within a given day, if one messenger was assigned a delivery, another messenger will end up with one less delivery. This leads to negative correlation of the residuals within a day, rendering OLS standard errors too large. On the other hand, there could be positive correlation in ε_{it} for observations coming from a given messenger, rendering OLS standard errors too small (see Bertrand, Duflo and Mullainathan, 2004, for an extensive discussion). As a consequence, we estimate two sets of standard errors. One set is adjusted for “clustering,” or correlation, in the error term across days. Because this ignores the (potentially) positive correlation within individuals, we consider these standard errors the lower bounds. The other is adjusted for clustering on messengers. We consider this the upper bound on the standard errors, because it ignores the (potentially) negative correlation within days. However, our basic conclusions do not depend on which adjustment of standard errors we use.

⁸ Because our dependent variable is bounded below by zero, this necessarily implies that the variance of the error term differs between observations.

4. Results

4.1 Analysis of Delivery Records

Figure 3 summarizes the results from our regression analysis using the delivery records of firms A and B. The figure plots the values of the γ^k regression coefficients, multiplied by 50 to illustrate the impact of a \$50 windfall gain. All coefficients are statistically significant at the 1 percent level, except for the coefficient for the first hour of the afternoon at Firm A, which is not significant.

Figure 3 shows that windfall gains in the morning have a statistically significant impact on the effort profile in the afternoon, contrary to the predictions of the standard, cognitive model of labor supply. On the other hand, the response of effort to the windfall gain is consistent with messengers attaching affective significance to a daily earnings goal. As predicted by the alternative model of labor supply, a messenger with a windfall gain works harder than other messengers in the first part of the afternoon, but less hard later in the day. Furthermore, the fact that the relative difference in effort is increasing over the first few hours is consistent with the goal gradient prediction of the model and not with an explanation based on fatigue from the morning.⁹

⁹ These findings are also broadly consistent with the predictions of the reference-dependent model of labor supply in Koszegi and Rabin (2005), which predicts that an unexpected increase in morning earnings can lead to a drop in effort in the afternoon. However, their model has only two periods, morning and afternoon, and thus cannot predict the goal gradient that we observe. This reflects the different focus of their

Our results are also consistent with previous studies, which conclude that daily earnings goals influence the effort decisions of piece rate workers. These studies have focused on the impact of day-to-day variation in wages on total daily effort, and have found that higher wages lead to lower daily effort, consistent with workers achieving a daily earnings goal more quickly under the high wage (e.g. Camerer *et al.*, 1997, Chou, 2003; Fehr and Goette, 2007). With the exception of Goette and Huffman (2005), however, these studies have not been able to observe within-day effort profiles and thus have not been able to test for the goal gradient effect. Goette and Huffman (2005) study the impact of exogenous increases in the piece rates at two bicycle messenger firms and find that messengers on the high piece rate work harder earlier in the day, but less hard later in the day, than messengers of the low piece rate, consistent with the evidence on the goal gradient effect presented in this chapter.

4.2 Survey evidence

An advantage of conducting a survey is that we can ask messengers directly whether they have earnings goals that are relevant during the workday. Accordingly the survey included the following question:

After earning ____ dollars during the day, it feels less urgent to earn another dollar (if this question does not apply to you, answer with N.A.)”

Of the messengers surveyed, 73 percent responded that they have such a dollar amount in mind during the day. The survey also asked, “*What is the minimum amount you need to*

research, on modeling the role of expectations in determining the reference point, rather than the role of affect as a source of motivation to work towards a reference point.

earn in a day, to make it worthwhile to come to work?" With only a few exceptions, this minimum amount is below the amount a messenger reports in the first question, consistent with the first question measuring an earnings goal that is distinct from a daily minimum.

Another question in the survey presented respondents with a hypothetical scenario, which was designed to correspond to our analysis of the delivery records. The question describes two scenarios: in one scenario, the messenger has had a "good" morning, earning much more than average; in the other scenario the messenger has had a "slow" morning, earning much less than average. The question states that the messenger worked equally hard in the two scenarios, and that in either case the afternoon is expected to be good. This establishes a difference in earnings across the scenarios due to windfall gains, and not due to effort. The question then asks the messenger to fill in the following statement, using a scale that goes from "much less" to "much more:"

"After the slow morning, I care ____ about earning another dollar, relative to after the good morning."

In the survey responses, 18 percent of messengers say they care the same, 72 percent say they care more, and 10 percent say they care less about earning another dollar after the slow morning. This is consistent with the majority of the messengers being loss averse around a daily income goal: a good morning puts a worker close to their daily target and leads to lower marginal utility of income in the afternoon. Because the question keeps morning effort constant across both scenarios, fatigue does not appear to explain why messengers say they would work less hard after a good morning.

5. Conclusion

The standard economic model assumes that an individual working on a long-term project decides how hard to work, and when, based on a purely cognitive calculation of costs and benefits. By contrast, this chapter argues that affect is an additional, important source of motivation. Building on evidence from neuroscience, we propose a new, dual-process model of working towards a long-term project, which maintains the standard assumption in economics, that the individual's cognitive processes are sophisticated and forward-looking, but allows for circumstances in which affective processes can override cognitive priorities and distort the individual's effort profile. In particular, the individual's daily performance is assumed to have an affective significance, depending on how it compares to a personal goal or reference level. Consistent with evidence from neuroscience, the affective system is assumed to value effort more highly when the individual has not yet achieved this more narrowly-defined goal. Furthermore, the affective system is assumed to become increasingly aroused as the goal becomes more immediate, leading to the prediction of an increasing effort profile, or goal gradient, leading up to a goal.

The alternative model is able to explain important facts about effort decisions in the workplace, which are difficult to explain from a purely cognitive perspective. One example is the new evidence of a goal gradient presented in this chapter. Using data on the within-day effort profiles of bicycle messengers, we show that a windfall gain in morning earnings causes a messenger to work harder in the first portion of the afternoon, relative to other messengers, but less hard later in the afternoon. This pattern is inconsistent with a purely cognitive model, because a windfall gain in the morning does not affect the financial incentives to work in the afternoon (and leads to only a small

change relative to the long-term income goals of the worker). On the other hand, the pattern is consistent with the lucky morning pushing the messenger closer to a daily income goal, triggering the goal gradient and leading to more intense effort early in the afternoon. Later in the afternoon, when other messengers are still approaching their goals, the lucky messenger may have already surpassed the goal and thus work less hard. Another example is the important finding in previous studies that a worker's total daily effort is often unchanged, or even decreases, in response to a temporary increase in the wage. This contradicts a central prediction of a purely cognitive model that a worker should work harder when financial incentives are high. The alternative model can explain this perverse effect of financial incentives, however, because it allows for affective, as well as financial valuation of effort: a higher wage allows a worker to reach a daily earnings goal more quickly, and thus causes the affective valuation of effort to drop earlier in the day. If affect was a sufficiently important component of the worker's motivation to begin with, reaching the goal earlier can lead to a net drop in total daily effort.

The broader theme of this volume is whether affect leads to better or worse decisions. The answer to this question depends partly on the benchmark used. In our model, affect causes the worker to work too hard when a narrowly-defined goal is close, and not hard enough when the goal is surpassed, compared to a purely cognitive perspective where effort should be constant over time. For welfare calculations, our starting point is the premise that the affective system's payoff should be ignored. To be sure, affective experiences, e.g., anticipated joy from completing the project (being awarded the degree, reaching the desired BMI), inform the cognitive system in important

ways about whether to engage in the project in the first place. The focus of our analysis, however, was on how to best work on such projects, and for this perspective, we argue that the payoff to the affective system should be ignored. We thus conclude that affect distorts decisions relative to the optimal benchmark. However, how severe these distortions are critically depends on the narrowly-defined goal.

We have so far sidestepped the issue of where these goals come from. We can imagine different sources of these goals, and they matter to judge the welfare loss due to the affective system's influence on behavior. One possibility, a straightforward extension of our model, is to integrate a conscious choice of these goals by the individual herself. One approach would be to let the cognitive system set the goal before the workday / workout starts, and the (partly randomly determined) productivity of effort is known. The cognitive system could then choose a goal for the affective system that will result in an effort allocation that is closest to what the cognitive system would desire in the absence of affective distortions of effort choices. It is obvious that too low or too high goals are not optimal, as they make the affective system complacent (if the goal is surpassed without any effort), or desperate (if the goal is so high, no effort level can reach it), making the distortions in the effort profile strongest. A goal that minimizes the average distortions caused by the affective system will be optimal. Thus, we predict that when individuals choose goals for themselves, affect will do comparatively little harm. In fact, such a model also gives a rationale why individuals may set narrowly-defined, daily goals for themselves and not broad, monthly goals. If the affective system is strongly influenced by the proximity to the goal, medium-run, e.g., monthly, goals may create larger distortions in effort than short-term, daily goals.

As a second possibility, one can envision a model where a third party sets the goal for the individual. The evidence we reviewed, and a much broader literature (Locke and Latham, 1990), are consistent with the interpretation that others can also influence the affective system's target. An area where our research could be applied fruitfully is to examine how firms may use goal-setting as an additional device to elicit effort from employees. Providing incentives using, e.g., pay-for-performance, is costly for the firm, hence goal setting to elicit effort may be an attractive, low-cost alternative. In this case, the firm has an incentive to set the goal such that the affective system is “freaking out” maximally, providing the highest possible overall effort. However, our analysis implies that such goal-setting exacerbates the negative impact of the affective system on the individual's welfare. Firms will have to at least partly compensate workers for this through a higher fixed salary, but the firm will set more challenging goals than the individual would choose for himself. To summarize, the extent of damage done by the affective system depends on who chooses the narrowly-defined goals. If the individual himself gets to choose the goal, our model predicts that the goal will be chosen such as to minimize damage done by the affective system. However, third parties, specifically, employers, may have incentives to use the goal strategically to their advantage, exacerbating the distortions by the affective system.

References

- Baumeister, Roy F. and Kathleen D. Vohs (2003). "Willpower, Choice, and Self-Control," in George Loewenstein, Daniel Read and Roy F. Baumeister, eds., *Time and Decision: Economic and Psychological Perspectives on Intertemporal Choice*. New York: Russell Sage Foundation, 201-216.
- Benhabib, Jesand Alberto Bisin (2004). "Modelling Internal Commitment Mechanisms and Self-Control: A Neuroeconomics Approach to Consumption-Saving Decisions." Mimeo, New York University.
- Bernheim, B. Douglas and Antonio Rangel (2003). "Emotions, Cognition, and Savings: Theory and Policy." Mimeo, Stanford University.
- Bernheim, B. Douglas and Antonio Rangel (2004). "Addiction and Cue-Triggered Decision Processes." *American Economic Review*, 94(5), 1558-1590.
- Bertrand, Marianne; Duflo, Esther and Mullainathan, Sendhil (2004). "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*, 119(1), 249-75.
- Camerer, Colin, Linda Babcock, George Loewenstein and Richard Thaler (1997). "Labor Supply of New York City Cabdrivers: One Day at a Time." *Quarterly Journal of Economics* 112(2), 407-41.
- Chen, Keith M., Venkat Lakshminarayanan, and Laurie Santos (2005). "The Evolution of Our Preferences: Evidence from Capuchin Monkey Trading Behavior," unpublished manuscript, Yale university.
- Chou, Yuan K. (2002). "Testing Alternative Models of Labor Supply: Evidence from Cab Drivers in Singapore." *The Singapore Economic Review* 47(1), pp. 17 – 47.
- Cohen, Jonathan D. (2005). "The Vulcanization of the Human Brain: A Neural Perspective on Interactions Between Cognition and Affect and Optimality in Decision Making." Working Paper, Department of Psychology, Princeton University.
- Farber, Henry (2005) "Is Tomorrow Another Day? The Labor Supply of New York City Cab Drivers," *Journal of Political Economy*, 113, 46-82.
- Fehr, Ernst and Lorenz Goette (2007). "Do Workers work more when Wages are High? Evidence from a Randomized Field Experiment.", *American Economic Review*, forthcoming.

- Goette, Lorenz and David Huffman (2005) "Incentives and Within-Day Effort Profiles: Evidence from Natural Experiments with Bicycle Messengers, unpublished manuscript, Univ. of Zurich.
- Goette, Lorenz, David Huffman and Ernst Fehr (2004) "Loss Aversion and Labor Supply," *Journal of the European Economic Association*, 2(2-3), 216-228.
- Heath, Chip, Richard Larrick, and George Wu (1999). "Goals as Reference Points." *Cognitive Psychology* 38, pp. 79-109.
- Heilizer, Fred (1977) "A Review of Theory and Research on the Assumptions of Miller's Response Competitions Model: Response Gradients," *The Journal of General Psychology*, 97, 17-71.
- Kahneman, Daniel and Amos Tversky (1979) "Prospect Theory: An Analysis of Decisions Under Risk," *Econometrica*, 47, 263-291.
- Kivetz, Ran, Oleg Urminsky, and Yuhuang Zheng (2005) "The Goal Gradient Hypothesis Resurrected: Purchase Acceleration, Illusionary Goal Progress, and Customer Retention," forthcoming in the *Journal of Marketing Research*.
- Koszegi, Botond and Matthew Rabin (2005) "A Model of Reference-Dependent Preferences," unpublished manuscript, UC Berkeley.
- LeDoux, Joseph E. (1996). *The Emotional Brain: The Mysterious Underpinnings of Emotional Life*. New York, NY: Simon and Schuster.
- Locke, E.A. and G. P. Latham (1990), *A Theory of Goal Setting and Task Performance*. Englewood Cliffs, NJ: Prentice-Hall.
- Loewenstein and O'Donoghue (2005). "Animal Spirits: Affective and Deliberative Processes in Human Behavior," unpublished manuscript, Cornell University.
- MacLean, Paul D. (1990). *The Triune Brain in Evolution: Role in Paleocerebral Function*. New York: Plenum.
- Manuck, Stephen B., Janine D. Flory, Matthew F. Muldoon, and Robert E. Ferrell (2003). "A Neurobiology of Intertemporal Choice," in George Loewenstein, Daniel Read and Roy F. Baumeister, eds., *Time and Decision: Economic and Psychological Perspectives on Intertemporal Choice*. New York: Russell Sage Foundation, 139-172.
- Massey, Douglas S. (2002) "A Brief History of Human Society: The Origin and Role of Affect in Social Life." *American Sociological Review*, 67, (1), 1-29.

- McClure, Samuel M., David Laibson, George Loewenstein, and Jonathan D. Cohen (2004). "Separate Neural Systems Value Immediate and Delayed Monetary Rewards." *Science*, 306(Oct 15), 503-507.
- Metcalf, Janet and Walter Mischel (1999). "A Hot/Cool-System Analysis of Delay of Gratification: Dynamics of Willpower." *Psychological Review* 106(1), 3-19.
- Mischel, Walter, Ebbe B. Ebbesen, and Antonette Zeiss (1972). "Cognitive and Attentional Mechanisms in Delay of Gratification." *Journal of Personality and Social Psychology*, 21(2), 204-218.
- Mischel, Walter, Ozlem Ayduk, and Rodolfo Mendoza-Denton (2003). "Sustaining Delay of Gratification over Time: A Hot-Cool Systems Perspective," in George Loewenstein, Daniel Read and Roy F. Baumeister, eds., *Time and Decision: Economic and Psychological Perspectives on Intertemporal Choice*. New York: Russell Sage Foundation, 175-200.
- Mischel, Walter, Yuichi Shoda, and Monica L. Rodriguez (1989). "Delay of Gratification in Children." *Science*, 244(4907), 933-938.
- Nielson, William S. (2002) "Comparative Risk Sensitivity with Reference-Dependent Preferences," *The Journal of Risk and Uncertainty*, 24(2),131-42.
- See, Kelly E., Chip Heath and Craig Fox (2003) "Motivating individual performance with challenging goals: Is it better to stretch a little or a lot?" Working Paper, Fuqua School of Business.
- Satpute, Ajay B. and Matthew D. Lieberman (2004), "Integrating Automatic and Controlled Processes into neurocognitive models of social cognition", *Brain Research* 1079, pp. 86 – 97.
- Shidara, Munetaka, Thomas G. Aigner, and Barry J. Richmond (1998) "Neuronal Signals in the Monkey Ventral Striatum Related to Progress through a Predictable Series of Trials," *The Journal of Neuroscience*, 18(7), 2613-2625.
- Shidara, Muntetaka and Barry J. Richmond (2002) "Anterior Singulate: Single Neuronal Signals related to Degree of Reward Expectancy," *Science*, 296, 1709-1711.
- Shiv, Baba, George Loewenstein, Antoine Bechara, Hanna Damasio, and Antonio Damasio (2005). "Investment Behavior and the Dark Side of Affect." Mimeo, University of Iowa.
- Thaler, Richard H. and Hersh M. Shefrin (1981). "An Economic Theory of SelfControl." *Journal of Political Economy*, 89(2), 392-406.

Tom, Sabrina, Craig Fox, Christopher Trepel, and Russell Poldrack (2007), “The Neural Basis of Loss Aversion in Decision-Making under Risk”, *Science* 315, pp. 515 – 518.

Tversky, Amos and Daniel Kahneman (2000). *Choices, Values, and Frames*. Cambridge, MA: Cambridge University Press.

Wu, George, Chip Heath, and Richard Larrick (2002) “A Value-Function Based Model of Goal Behavior,” unpublished manuscript, Univ. of Chicago Graduate School of Business.

Figure 1

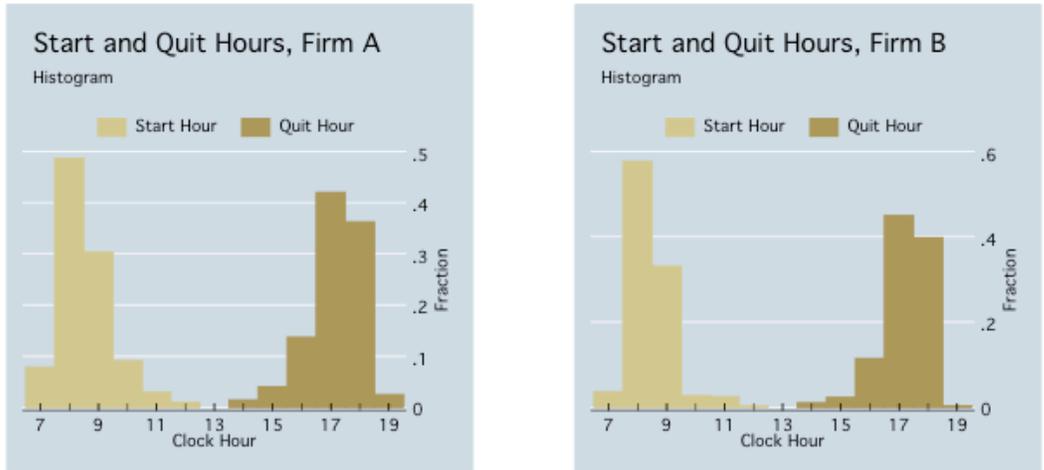


Figure 2

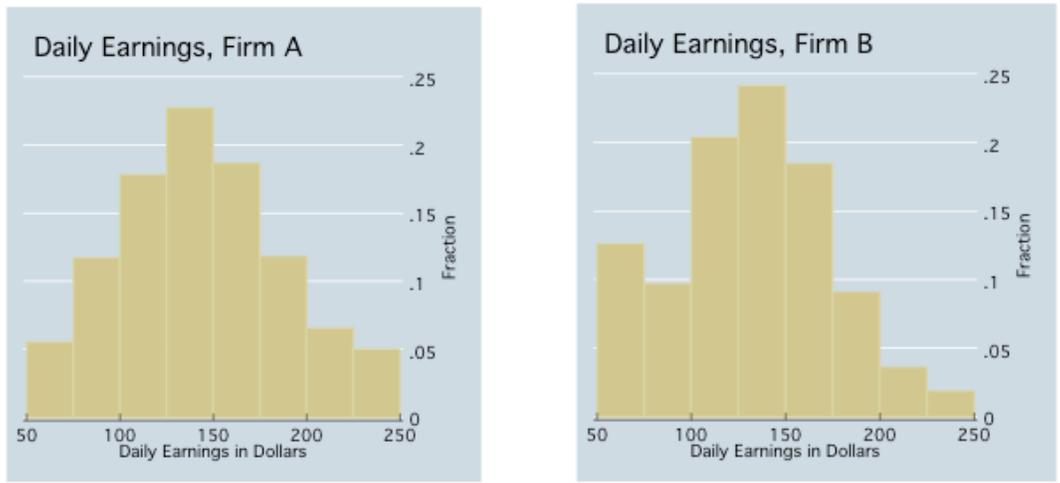


Figure 3

Effort over Time: The Impact of a \$ 50 increase in morning revenues (+ / - 2*s.e. of estimate)

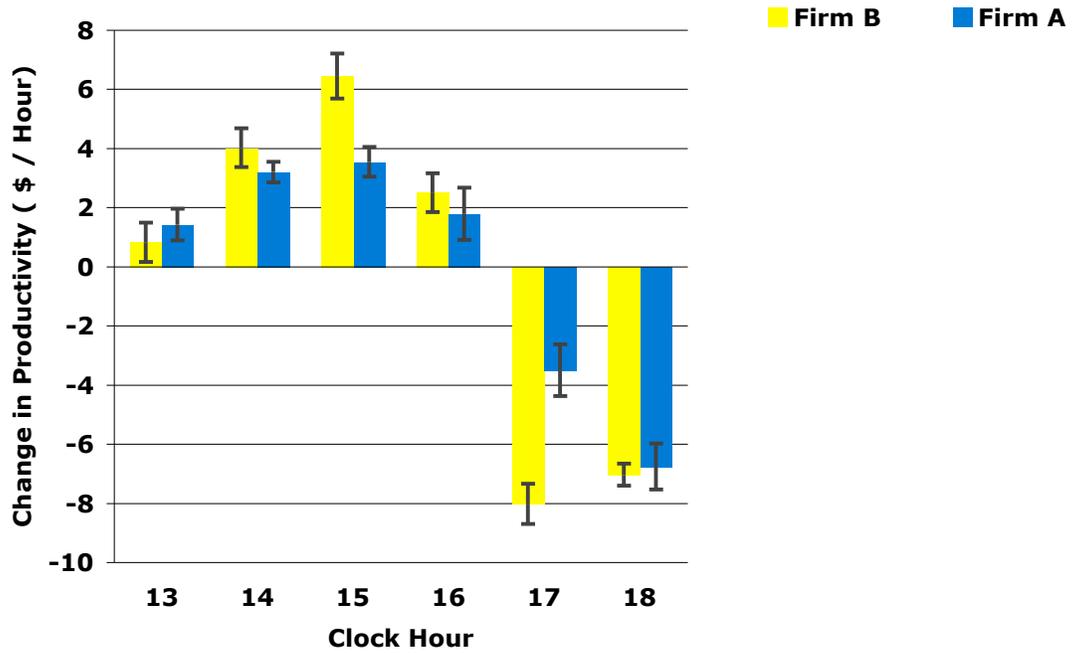


Table 1
Hours on the Job

Firm A		Firm B	
6-	1.39%	6-	0.94%
7	3.30%	7	1.45%
8	8.73%	8	4.55%
9	24.39%	9	20.34%
10	40.34%	10	53.63%
11+	21.85%	11+	19.00%

Table 2
ANOVA for Morning Earnings

	Firm A	Firm B
	Adjusted R-squared	
Date Fixed Effects	.1238	.1000
Date and Messenger Fixed Effects	.3106	.5983
SD of Unexplained Variance (as % of average morning earnings)	33.04%	28.69%
Observations	21,474	22,866