Time Preference and Technology Adoption: A Single-Choice Experiment with U.S. Farmers

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Abstract: We elicit time-discounting behavior from U.S. farmers that are broadly known to be either late or early adopters of farming best management practices. Using a single-choice experiment, we estimate the mean discount rate for each farmer group and find that late adopters have a mean discount rate that is thirteen percentage points higher than the mean rate of early adopters. We argue through simulations that this difference is likely due to differences in time preference rather than risk aversion.

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1. Introduction

Technology adoption is key to economic growth and an important component of individual economic activity. Time preference – how individual consumers and entrepreneurs weigh current versus future rewards – is likely crucial to understanding technology adoption because of the up-front investments it entails to obtain future returns. Yet while there are many empirical studies of the factors that lead individual companies or individual consumers to adopt new technologies, few of these provide a clear account of the role of time preference.[1] The difficulty is largely one of observation – time preferences are not easily observable in non-experimental settings because the observed choices are the result of a complex interaction of other underlying preferences, unobserved investment returns, and possible market constraints.

In this paper, we conduct a field experiment to elicit time preferences from two samples of U.S. farmers who are known to be early- and late-adopters of "best management practices," a set of management strategies that build long-term soil productivity. Subjects were asked to make a single choice between an early payment and a larger, later payment; following the literature, we used variations in the later payment to infer mean discount rates. The field experiment was carefully designed to look "realistic" to the subjects[2]. We find that the late-adopters have mean discount rates that are 14 percentage points higher than the early-adopters.

Even in experimental settings, however, the isolation of discount rates can be challenging. Recent methodological advancements in the literature seek to separate the reduced-form time preference over money into the separate effects of discount rates and risk aversion. We argue below that these papers have introduced assumptions that accentuate the role of risk aversion. When these assumptions are relaxed even slightly, the role of risk aversion is reduced. When these assumptions are fully relaxed (in a sense to be made precise below), the estimates derived from payment-timing experiments such as ours come close to identifying true discount

[1] See Chavas et al. (2010) and Sunding and Zilberman (2001) for a broad review of factors important to farm production and technology adoption.
[2] Harrison and List (2004) refers to this type of experiment in a non-lab setting with realistic choices as a "natural" field experiment.

rates, even without accounting for risk aversion.

Our argument is as follows. When individuals receive payments, they convert these into consumption flows, which are the true source of utility. Most of the previous experimental research has assumed that individuals consume their payments over a short period of days. For instance, Andersen et al. (2008) report sensitivity checks for their results for a duration of consumption over a range of 14 days. The authors show that the 1 day period maximizes the log-likelihood of their econometric model and chose to report their main results under the assumption of 1 day so as to provide a more direct comparison with the existing literature. Likewise, Andreoni and Sprenger (2012) report estimates of their implied discount rates only for a consumption duration assumed to be 1 day. When payments are consumed so quickly, they become a substantial addition to the individual's background consumption and utility curvature (that is, risk aversion) plays a strong role in the utility the individual experiences from the experiment's payments.

We argue, however, that a one-day or one-week period of consumption is unrealistically short when payment sizes are as large as in Andersen et al. (2008) and our own experiment. When individuals are instead assumed to consume the payments over a more reasonable time period, or when more risk averse individuals are allowed to spread the payments over a greater length of time, as they want to do, then the role of risk aversion is considerably diminished. The bottom line is that the assumption of risk neutrality does not cause a substantial overstatement of discount rates in payment-timing experiments. In the context of our technology adoption results, this finding means that late-adopters likely have higher discount rates than early-adopters and, equivalently, that their greater likelihood to choose "now" payments results mainly from true impatience and not greater risk aversion.

The link that we establish in this paper between time preferences and technology adoption in agriculture is an important one. Between 1960 and 2004, productivity changes in the farming industry contributed to 12.1 percent of total factor productivity growth (TFP) in U.S. private industry (Fuglie et al., 2007; Jorgenson et al., 2007). As a percent of industrial growth, TFP accounted for 117 percent of the growth in agricultural output, while just 13 percent in all other industrial output. While these figures show impressive gains from new technology in the aggregate, many empirical studies find that cost-effective technologies are often either not adopted by producers (or consumers) or adopted very slowly, leading to what the energy economics field describes as the "energy paradox" (Jaffe and Stavins, 1994) or the "energy efficiency gap" (Allcott and Greenstone, 2012) due to "investment inefficiencies." Our results suggest that reductions in the efficiency gap and increases in productivity in the farm sector could be achieved by policies that provide a better mixture of time-delineated incentives to help overcome individual impatience.

2. The Role of Time Preference in Technology Adoption in the U.S. Farming Industry

Crop farming relies on a number of decisions about crop variety, tillage method, fertilizer (characterized by type, rates, timing, and application method), pesticide use, as well as whether to put land under production or leave it as buffers, fallow, or natural land. Livestock farming relies similarly on decisions about feeding rations, breeding, and pasture management. For each of these decisions, new varieties, technologies, and farming methods become available periodically and farmers must choose when to adopt newly available options. Many of these options, such as reduced tillage intensity, have short-term costs (both in terms of fiscal costs for new equipment and the opportunity cost of "mistakes" made as the farmer adjusts crop grown or planting time) but long-term benefits in terms of greater soil productivity.[3] A plausible reason for the slow adoption of some technologies is the timing of benefits and costs associated with new technologies. Basic theory suggests that individuals with higher discount rates will be less likely to adopt new technologies with benefits that occur in the future but that require relatively large up-front investment costs.

Despite the apparent importance of discounting behavior, there is little supporting evidence for its role in the technology adoption of farmers and, more broadly, to farming decisions. Some existing studies use indirect measures of time preference such as whether a farmer intends to transfer the farm to a child (Ervin and Ervin, 1982) or a hypothetical survey question on the farmer's level of patience (e.g., Holden et al., 1998; Shiferaw and Holden, 1998; Teklewold and Köhlin, 2011). Other studies rely on market-level transactions to infer the underlying discount behavior that would rationalize the observed adoption behavior. These

[3] The farming practices that distinguish our samples are not truly new but they do represent changes over how farms typically would have been managed in past decades. Given that the practices are new in this context, it makes sense to refer to BMPs as "technology adoption" because they share the features of the technology adoption literature, even if they do not involve technological innovations.

studies must often rule out other sources of influence with assumptions that may not actually hold in a market-setting (Abdulkadri and Langemeier, 2000; Barry et al., 1996; Lence, 2000).

Our results are most directly related to the findings of Yesuf (2004) and Duflo et al. (2011), studies that highlight the relationship between the time preference of farmers and their production decisions. The field experiment in Yesuf (2004) elicited discount rates from 262 farm household heads and correlated these discount rates to adoption of soil conservation technology. Farmers in the study were found to have a mean discount rate of 42 percent (compounded annually), and higher discount rates were found to be significantly correlated with reduced adoption of soil conservation technology. Duflo et al. (2011) found that farmers in Western Kenya behaved consistent with a model of myopia by failing to make profitable investments in fertilizer purchases because of (uncontrolled) impatience.[4]

Empirical studies have identified other characteristics associated with technology adoption such as farmer age, education levels, and tenure, and farm operation size (e.g., Ervin and Ervin, 1982; Featherstone and Goodwin, 1993; Wu and Babcock, 1998). Most of these factors do not truly identify the underlying utility-theoretic or behavioral parameters they are presumed to represent (e.g., education levels). Theoretical models have been better able to model the effects of utility parameters on technology adoption and have shown, for instance, that irreversible investments and the timing of the resolution of uncertainty about future benefits of a technology can result in the counterintuitive effect of higher rates of time preference leading to adoption sooner rather than later (Doraszelski, 2001; Farzin et al., 1998; Isik, 2004; Isik and Yang, 2004).

3. Experimental Elicitation of Time Preference

3.1. Methodological Approaches

Previous experimental studies of time preference have used both open-ended ("How much would you pay now to receive $100 in one year?") and closed-ended ("Would you prefer $95 now or $100 in one year?") elicitation formats (see early studies by Thaler (1981), Fuchs

[4] In a study of risk and time preferences, Tanaka et al. (2010) find that experimentally-elicited discount rates from Vietnamese rice farmers are negatively correlated with the farmer's income, suggesting that high levels of average impatience could partially explain the lower welfare outcomes of some communities. There are other experimental studies which provide evidence for the role of time preference in predicting a wide range of other economic outcomes such credit card borrowing (Meier and Sprenger, 2010) and addiction (Kirby et al., 1999).

(1982), and Horowitz (1991); for a voluminous review see Frederick, Loewenstein, and O'Donoghue (2002).) Recent studies have used a type of closed-ended format similar to the multiple price list (MPL) format for estimating risk aversion in Holt and Laury (2002) (e.g., Coller and Williams, 1999; Harrison et al., 2002; Pender, 1996). In an MPL procedure, subjects receive a list of choices between two payment options that have different size payments that occur at different times. For instance, an individual may be asked to choose between receiving \$100 now versus \$100+*X* one year from now, with *X* varying over ten binary payment choices.[5]

Recently, Andersen et. al. (2008) have suggested that discount rates can be significantly overestimated from payment choice data if the effect of risk aversion is not taken into account.[6] The impact of the Andersen et al. paper on methodological approaches has been substantial; many recent authors have either adopted a dual-elicitation task to account for both time preference and risk aversion (Andreoni and Sprenger, 2012) or devised creative work-arounds to avoid the compounding effect of risk aversion on implied discount rates (Laury, et al., 2012).

3.2 Our Procedure: Sample Groups

Our field experiment elicited discount rates from a sample of 208 U.S. farmers. In June 2011, American Farmland Trust (AFT) selected names from its lists of two recent programs, the *Best Management Practice Challenge* (BMPC) program and a series of listening sessions focused on water quality trading. The BMPC specifically targets farmers who have yet to adopt conservation production practices such as no-till farming or reduced nitrogen application and thus is composed primarily of late adopters of new agricultural practices.[7] The second group of farmers were on the mailing list for AFT's "listening sessions" (LS) to help develop and encourage water quality trading and other possible environmental markets. The LS farmers were generally known by AFT to have adopted some best management practices, shown interest in water quality trading, or otherwise taken an early initiative to improve agricultural and environmental performance. Thus, farmers in the experiment are *a priori* known to be either late or early adopters of farming best management practices. AFT has devoted considerable attention

[5] There are other methods of introducing variation in the evaluation of payments. Instead of varying payment size, the horizon between payments could vary. In addition, (Laury et al., 2012) show that payments can be assigned with probability.

[6] The authors find the estimated average discount rate of the Danish population decreases from 25 percent to 10 percent after accounting for individual levels of risk aversion under a consumption duration of 1 day.

[7] See http://www.bmpchallenge.org/ for details.

to identifying and reaching particular farmer archetypes—the BMPC is a program that specifically targets individuals who have not yet adopted widely available conservation technologies, whereas LS is a program that draws in farmers with an active interest in up-and-coming farming issues. Thus it is likely that this division of the sample represents a meaningful split in farmer attitudes and attributes, and not just a matter of judgment.

The BMPC targets farmers through independent crop advisors. Crop advisors see the BMPC as an enticement that they can use in order to convince reluctant farmers to try new technologies. AFT has conducted a host of different "challenges" over the years, each tailored to a particular resource concern and technology. For example, in areas where nitrogen runoff and pollution is a resource concern, AFT has deployed a "challenge" to farmers (through the crop advisors) to reduce nitrogen application to recommended rates. Farmers who accept the challenge dedicate some portion of their land to production using agronomic (recommended) rates of nitrogen application. "Test strips" which are adjacent to this land and on which farmers can apply their normal production practices are used as an experimental comparison. If yield falls on the "challenge" land (as compared to the test strips), AFT reimburses the farmer for any loss in profits. The identification of farmers who participate in this program as *late adopters* is accomplished by the crop advisors – individuals in private practice who know the farmers in their territory well and target their advice and services to the preferences of farmers.

By contrast, farmers who take part in AFT listening sessions are, by virtue of their participation, going out of their way to be progressive. We did not survey LS farmers about their production practices, but based on interviews with AFT staff and attendance at listening sessions by the authors, we are comfortable asserting that these farmers were, on the whole, unusually progressive adopters of conservation technologies (exactly the kind of technologies that the BMPC targets). It is not necessary, however, to view the LS farmers as early (left-tail) adopters. The distinction we make is between late adopters and the LS group. This distinction rests on the identification of BMPC participants as late adopters. This identification is made by many independent crop advisors enrolling participants in a long-running and successful program.

3.3 Elicitation Procedure

The lists of names for potential LS and BMPC participants were checked for duplicates across programs (1 observation) or multiple names at the same address, as might happen if a husband and wife or two brothers (presumably joint farm decision-makers) were included on the list (16 observations). Of the 310 initial names available from the two mailing lists, 293 payment choice experiments were mailed to individual farmers.

Each addressee first received a postcard telling them that they would soon be receiving a letter from AFT that would offer a payment of roughly $400. This postcard was designed to help ensure that no farmer mistook the eventual payment letter for junk mail. The payment letter followed a week later. It explained the reason for the payment (see below), listed the payment choice, and described the procedure for the individual to indicate his or her choice (logging into a website with a generic name or mailing their choice in an enclosed envelope.)

Subjects were offered a choice between a payment of $405 to be received in approximately two weeks, described as being made "right away (your check should arrive in the mail in approximately 15 days)," and a larger payment that would be made nine months later "at the start of the next growing season (your check will be mailed out March 1, 2012)." This timing exploited a natural break in the cycle of the farm year and was chosen to add to the realism of the payment choice. The later payment amount was the only aspect that differed across subjects. Farmers from each of the two lists were randomly assigned to one of three 9-month payment treatments. Treatments were assigned such that there were an equal number of subjects in each treatment.

The slight front-end delay on the now payment approximates the processing and mailing time of any type of payment that subjects might receive from an entity such as AFT. This delay conveniently equates transactions costs over the two time periods and reduces the potential effects from payment uncertainty (see Andreoni and Sprenger, 2012; Pender, 1996). A true "now" (zero delay) payment would have required a different payment mechanism, such as a pre-printed check.

3.4 Single-choice Elicitation Format: Discussion

Our experiment elicits time preference using a single-choice elicitation format. This approach mitigates framing effects, reduces respondent burden, and increases the saliency of the choice task. The single-choice format can be compared to the more common Multiple Price List (MPL) formats in which subjects make decisions over multiple pairs of payments, only one of which is played out for real money or formats that have subjects make allocation decisions between current and future wealth under alternative prices for making a transfer (e.g., Andreoni and Sprenger, 2012). The format of the choice task in our experiment is akin to subjects receiving just one random line from an MPL, i.e., any particular subject only sees one payment pair.

Under the single-choice format, experiments are limited to obtaining only a single bound on any individual's rate of time preference; thus the single-choice format sacrifices the ability to estimate rates more precisely, but avoids potential framing effects induced by the MPL. These framing effects arise because subjects facing an MPL see both a relative frame (by comparing pairs of choices which are ranked by the implied annual percentage rate of interest) and an absolute frame (by comparing the payments in a single choice). The relative impact of these two frames on measured discount rates is not well understood.[8] The single-choice format avoids the framing effect by completely excluding a relative frame from the elicitation format.

The single-choice format is also likely easier for subjects to understand than a series of choices and is likely to have a more natural context in that the decision is more similar to typical money decisions for a farmer than the MPL format. See Duquette, Higgins, and Horowitz (2012) for more details on the relative merits of the single choice and MPL formats.

4. Results: Estimated Differences in Average Discount Rates

We first estimate the average discount rate for the full sample of respondents when individuals are risk neutral (Model 1). Under risk-neutrality, the discounted utility of the early (14 days) and late (270 days) payments can be written as $PDU_0 = 1/(1+\delta)^{14/365} \times M_0$ and $PDU_t = 1/(1+\delta)^{270/365} \times M_t$, where M_0 and M_t are the payments received in 14 and 270 days, respectively. Subject i chooses the earlier payment option when $(PDU_{i0} - PDU_{it})/\sigma > \varepsilon_i$, where ε_i is an error term and σ is a noise parameter in the choice process. For large values of σ, the choice becomes inherently noisier and the probability that subject choose the early payment or the later payment becomes equally likely.

To identify the possible difference between the average discount rates of the LS and BMPC farmers, we allow δ to vary systematically with the use of an indicator variable for BMPC enrollment (*BMPC*) (Models 2 and 3). Under these specifications the average discount

[8] For futher discussion see Andersen et al.(2006), Andersen et al.(2007), and Harrison et al.(2007).

rate for a group is given by $\delta_{LS} + \delta_{\Delta} \cdot BMPC$, where the coefficient δ_{Δ} is the difference between the average discount rates of the LS and BMPC participants and δ_{LS} is the average discount rate for the LS farmers. We obtain the estimates $\hat{\delta}_{LS}$, $\hat{\delta}_{\Delta}$, and $\hat{\sigma}$ by maximum likelihood estimation under the assumption that ε is distributed standard normal such that the probability that an individual chooses the early payment is $Pr_{i0} = \Phi\big((PDU_{i0} - PDU_{it})/\sigma\big)$ and the log-likelihood of observed choices in our experiment is given by $\sum_N\big((\ln(Pr_{i0})|\ Choice_i = now) + (\ln(1 - Pr_{i0})|\ Choice_s = later)\big)$ where Φ is the standard normal distribution function. Model 3 further allows σ to vary across the two samples, with $\sigma = \sigma_{LS} + \sigma_{\Delta} \cdot BMPC$.

The estimated average discount rate over both LS and BMPC participants, denoted $\hat{\delta}_{LS+BMPC}$, is 0.41 (Model 1). This estimate is close to the vast majority of the experimental literature (Frederick et al., 2002) including the risk-neutral rates found in Harrison, et al. (2002) and Yesuf (2004) and the natural field experiments of Warner and Pleeter (2001) although it is much higher than studies that have inferred the rate from consumption and asset data (Abdulkadri and Langemeier, 2000; Barry, et al., 1996; Lence, 2000). It is also inconsistent with neoclassical optimization, as many papers have pointed out (e.g., Horowitz, 1991).

Models 2 and 3 present our main results. We find that the discount rates for our “late adopter” pool of farmers are substantially and significantly higher than discount rates for our “early adopter” pool. Estimated discount rates for BMPC farmers range from 0.49 to 0.59 and are 14 to 26 percentage points higher than discount rates for LS farmers, which range from 0.33 to 0.35, depending on whether the noise of the choice process is assumed to be the same for both groups (Model 2) or to differ between the two groups (Model 3).

Table 1. - Estimates of Discount Rates assuming risk neutrality

Estimated parameter	Model (1)	(2)	(3)
$\hat{\delta}_{LS+BMPC}$	0.41*** (6.59)	-	-
$\hat{\delta}_{LS}$	-	0.35*** (6.18)	0.33*** (6.70)
$\hat{\delta}_{\Delta}$	-	0.14* (1.66)	0.26 (1.17)
$\hat{\sigma}_{LS}$	70.20*** (3.78)	69.72*** (3.75)	59.84*** (3.32)
$\hat{\sigma}_{\Delta}$	-	-	44.31 (0.81)
Observations	206	206	206
Log-likelihood	-119.5	-117.8	-117.6

Notes: z-statistics are reported in parentheses and use robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

5. Are Late-Adopters Truly More Impatient?

5.1 Motivation

We argue in this section that greater risk aversion (that is, differences in utility curvature) is unlikely to be the reason we observe different choice patterns between the two groups and that late-adopters likely indeed have higher discount rates.[9] Our argument centers on assumptions about how the experimental payments would be consumed by recipients.

The existing experimental literature has modeled payments as being consumed over a small, exogenous number of time periods. Andersen et. al. (2008), for example, report their main estimates for a consumption duration of one day, although the authors also examine effects of consumption being spread over 14 days; in neither case do they allow the period to differ with individual risk aversion. As we demonstrate below, individuals are likely to want to smooth consumption over more than 14 days and more risk averse individuals will want longer smoothing periods. This smoothing substantially changes the role risk aversion plays in discount

[9] It is important to recognize that risk aversion in this context does not refer to uncertainty about future consumption or receipt of the future payment – it refers to risk averse individuals whose pleasure from the payment is dampened by having the consumption take place in a single period and who would prefer to smooth it out over time.

rate estimates.

To demonstrate these effects, we run simulations in which we allow individuals to smooth the consumption of the experimental payment over a longer time span than 1 or 14 days and allow more risk averse individuals to spread the payment over more periods – both reasonable modifications consistent with the spirit of this literature – and find that the role for risk aversion to influence the implied discount rate diminishes substantially. The reason for this result is that both a longer smoothing period and differential smoothing periods across individuals essentially "neutralize" the effect of risk aversion, leaving the individual with preferences that look close to risk neutral. The consequence is that the time dimension, which is the one aspect of payment choice that is most difficult for the consumer to compensate for, remains as the key element affecting individual choices. Thus, preferences over timing and not risk aversion are revealed by individual choices in our experiment.

5.2 *Results: Consumption Smoothing*

Define utility for the early payment M_0 as

$$(3)\qquad PDU_0 = \underbrace{\sum_{i=0}^{13}\left(\frac{1}{1+\delta}\right)^{\frac{i}{365}} U(\omega)}_{\substack{\text{stream of}\\ \text{background utility}}} + \underbrace{\sum_{i=14}^{14+\lambda-1}\left(\frac{1}{1+\delta}\right)^{\frac{i}{365}} U\left(\omega+\frac{M_0}{\lambda}\right)}_{\substack{\text{stream of}\\ \text{background utility}\\ \&\ \text{experimental payment}}} + \underbrace{\sum_{i=14+\lambda}^{T-1}\left(\frac{1}{1+\delta}\right)^{\frac{i}{365}} U(\omega)}_{\substack{\text{stream of}\\ \text{background utility}}}$$

and similarly for the later payment where δ is the individual's discount rate and ω is background consumption. Following Andersen et al. (2008), the individual spreads consumption evenly over λ periods and thus consumes M_i/λ per period over that time. Notice that our empirical results above were obtained under this specification of present discounted utility assuming risk-neutrality and a one day duration of consumption of the experimental payments ($\lambda = 1$). (Background consumption was irrelevant to our estimates under the assumption of risk neutrality.) We assume (as do Andersen et al.) that the individual applies the same λ to both the early and later payments; this assumption is reasonable because the difference between the λ's that maximize PDU_0 versus PDU_t is minuscule.

To see that setting $\lambda = 1$ may be suboptimal from the perspective of the individual, consider a CRRA utility function with a coefficient of risk aversion parameter ρ and let the individual optimize PDU_0 over λ for a range of ρ and ω values. Figure 1 shows the optimal λ's when we evaluate at the δ at which the individual is indifferent between the current payment of \$405 and future payment of \$498 for a range of ρ and ω values. Under this set-up, the risk neutral discount rate is roughly 34 percent.

Figure 1 demonstrates two important results. First, the optimal λ is more than 50 days for the vast majority of ρ and ω values and thus far above the short durations assumed in previous papers; under standard values of ω = 20 and ρ = 0.7 the optimal λ is over 100 days. Second, the optimal duration of consumption is increasing in risk aversion, as intuition suggests. [10]

We investigate the implications of higher assumed λ's and differential λ's across individuals on implied discount rates. To see the effects, we consider three modest, separate changes: (1) We set λ=50 for all individuals. This is clearly at the low range of optimal λ's but more realistic than the much lower λ's in the existing literature. This range is also close to the (scant) empirical evidence; Loewenstein and Prelec (1993) found that individuals planned to use a (hypothetical) restaurant coupon on average either 3 or 8 weeks after it was received. Our experimental payments are quite large relative to typical background consumption, which further suggests that λ=1 or even λ=14 is unrealistically low. (2) We allow λ to vary with ρ and set $\lambda(\rho) = 0.1\lambda^*(\rho)$ where $\lambda^*(\rho)$ is derived from Figure 1. That is, we allow more risk averse individuals to smooth consumption over longer periods but continue to keep these periods quite short, so as to compare the results to the existing literature. (3) We look at inferred discount when λ is fully optimal, i.e., $\lambda^*(\rho)$.

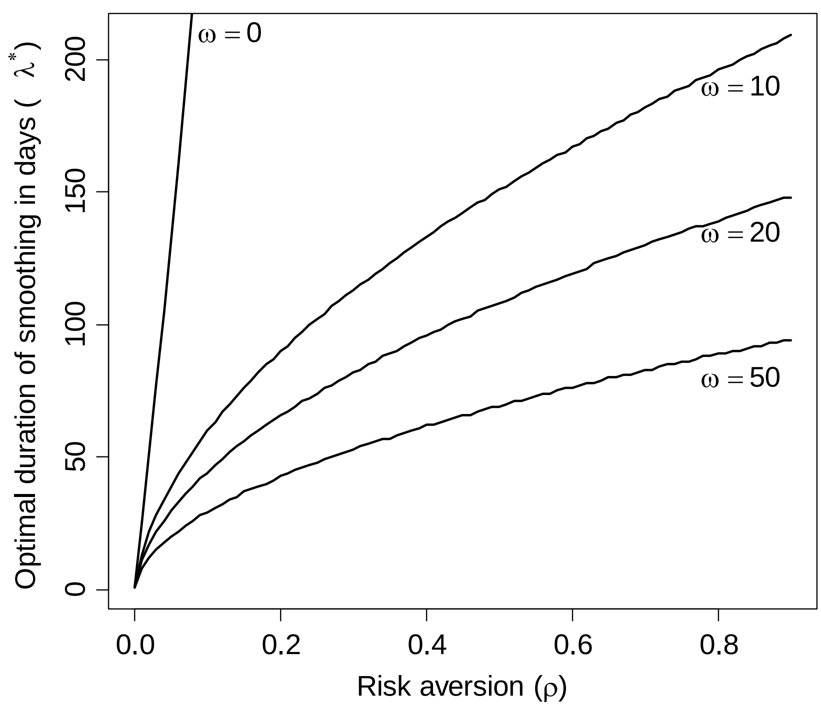
We chose these scenarios to stay within the spirit of the current literature. The time-preference elicitation literature relies heavily on individuals not fully optimizing their consumption paths. If individuals fully optimized – if they optimized both background consumption and any future payments (including borrowing against them) subject to a budget constraint – then the marginal rate of time preference should equal the market rate of return and would reveal, on its own, essentially nothing about the individual's discount rate or risk aversion, as Horowitz (1991) and others have remarked. Most of the estimated models therefore have instead assumed no optimization at all and have assumed constant background consumption and an exogenous consumption smoothing pattern; under these assumptions, individual choices

[10] Andersen et al. chose $\lambda = 1$ in part because it maximized the likelihood function based on their data. However, because λ and ρ should be correlated, such estimates are biased.

reveal bounds on underlying utility parameters. The more dimensions and directions along which the individual is assumed to optimize, the less informative the experiment becomes in revealing utility parameters albeit simultaneously more informative regarding the extent to which the individual optimizes.

Thus, to preserve the utility-revealing feature of payment choice, our analysis allows individuals to move in the desired direction in just one dimension – the number of periods over which the payment is consumed – and otherwise maintains most of the constraints imposed by existing papers. This dimension is the most natural constraint to relax, since it does not allow the individual to spend or even plan for the payment until it is actually received. A great deal of structure and "non-optimality" is maintained in the model; still, with this one change we see dramatic differences in the amount of time preference that it attributed to the discount rate rather than risk aversion.

Figure 1. Optimal Duration of Consumption Smoothing, $\boldsymbol{\lambda}^*$



Note: The optimal duration of consumption smoothing, λ^*, of experimental payments increases with the level of risk aversion, ρ. Individuals with higher background consumption, ω , choose lower consumption smoothing periods.

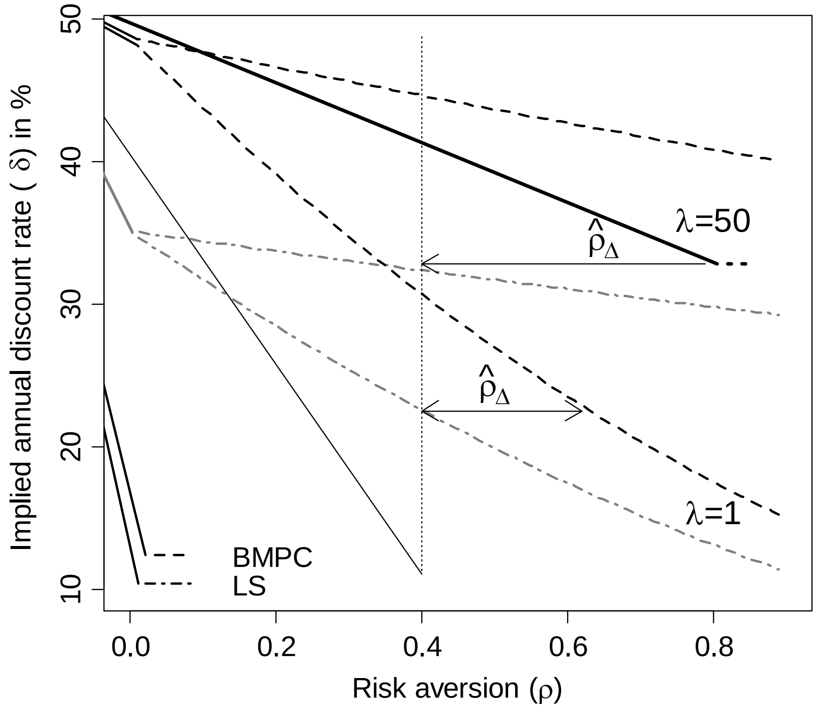
The results of the three scenarios are shown in Figures 2, 3, and 4. Each of the figures shows the set of $\{\delta, \rho\}$ that are consistent with the estimated risk-neutral discount rates found in Model 2, under different assumptions about λ and assuming background consumption = $20.[11,12] For example, LS farmers have an implied risk-neutral discount rate of δ = 0.35; this same behavior is consistent with δ = 0.34 and ρ = 0.4 when λ = 50. The Figures show a risk aversion range of $0 \leq \rho < .9$, which is consistent with existing literature. Holt and Laury (2002), for example, find 60 percent of their subjects have risk aversion levels (under CRRA) of $0.15 \leq \rho < 0.97$, with only 4 with $\rho > 0.97$. Andersen et al. (2008) find that 95 percent of the Danish population have a ρ between roughly 0.65 and 0.85 conditional on individual discount rates.

To see the role that consumption smoothing could possibly play in the observed difference between LS and BMPC choices, compare the dashed (BMPC) and dash-dot (LS) lines for a given λ (Figure 2). When λ =1 and when LS has ρ = 0.4, BMPC subjects need ρ approximately 0.25 points higher to have the same discount rate as LS, as shown by the lower $\hat{\rho}_{\Delta}$ in Figure 2. When λ =50, this same 0.25 point higher ρ for BMPC would yield a discount rate of 0.47 – in other words, still substantially higher than the LS discount rate. In fact, when λ =50, there is no level of risk aversion at which BMPC farmers would have an equal or lower discount rate than the LS farmers.

As Figure 2 shows, when λ = 1, BMPC farmers must be either substantially more risk averse or more impatient than LS farmers. When λ =50, BMPC farmers must necessarily be more impatient. Higher risk aversion is not enough.

[11] The set of $\{\delta, \rho\}$ can be thought of as alternative points along the line of indifference between the present discounted utilities of the early and late payments under an assumed value for the implied risk-neutral discount rate.
[12] We chose $20 because it was similar to previous values in the literature.

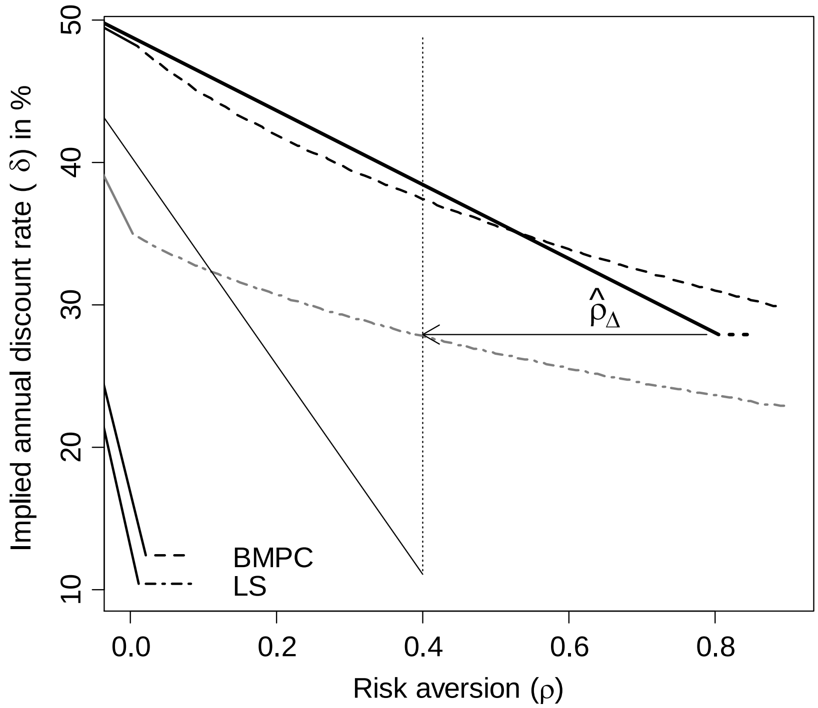
Figure 2. Fixed smoothing (λ = 50 & λ = 1)



Note: The necessary implied difference in risk aversion levels between the LS and BMPC farmers for the the discount rates to be the same for both groups would need to be implausibly large under long durations of consumption smoothing (λ = 50), but plausible under short durations of smoothing (λ = 1).

In scenario 2 (Figure 3), we allow more risk averse individuals to smooth the payment over more periods but continue to constrain all individuals to consume over relatively short periods – one-tenth of the duration they would optimally prefer. Again we find that when ρ = 0.4 for LS farmers, for example, there is no level of BMPC risk aversion at which BMPC farmers would have an equal or lower discount rate than the LS farmers. Figure 3 shows that even with our highly constrained individuals, the difference in risk aversion that is required for the Table 1 results to reflect higher risk aversion rather than higher discount rates is huge, if not non-existence.

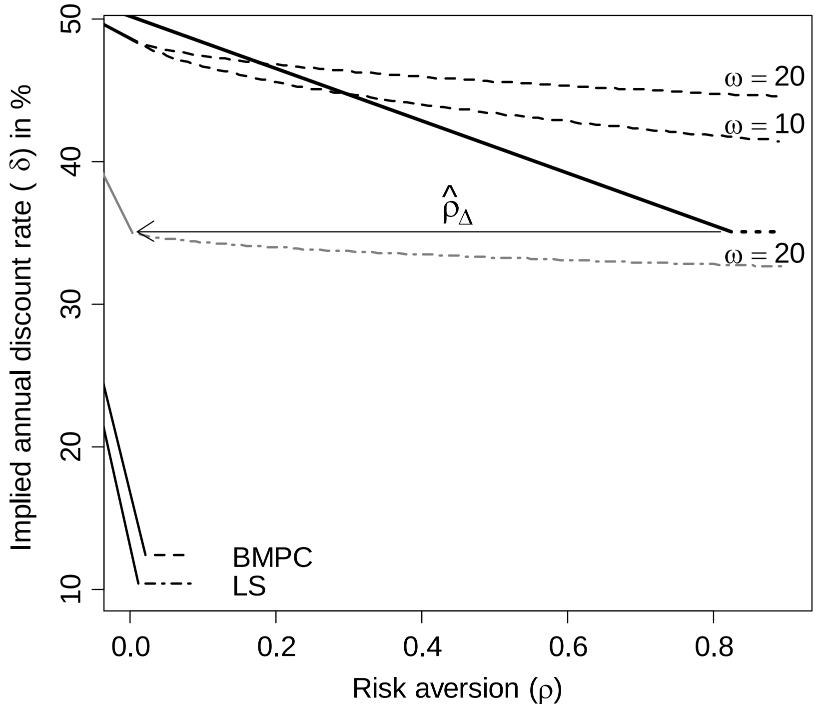
Figure 3. Differential smoothing, $\lambda = 0.1\ \lambda^*$



Note: The necessary implied difference in risk aversion levels to implied average discount rates that are equal for the LS and BMPC farmers would need to be very large under constrained differential smoothing, i.e., $\lambda = 0.1\ \lambda^*$.

Figure 4 shows the effects of allowing fully optimal smoothing . Since individuals want to smooth consumption over even longer periods than shown in Figure 2, the conclusions are even stronger: There is no level of risk aversion at which BMPC farmers would have $\delta < 0.46$.

Figure 4. Differential Smoothing, $\lambda = \lambda^*$



Note: The necessary implied difference in risk aversion levels to implied average discount rates that are equal for the LS and BMPC farmers would need to be implausibly large under optimal smoothing, i.e., $\lambda = \lambda^*$, even for plausible differences in background consumption.

5.3 Results: Background Consumption

Until now, we have assumed that the LS and BMPC farmers have the same levels of background consumption. Lower background consumption increases the role that risk aversion has and therefore decrease the implied discount rates (see Figure 4). Therefore, our results could be sensitive to the assumed equality of background consumption between the two groups.

Figure 4 shows the set of implied discount rates and risk aversion coefficients when the background consumption level of the BMPC farmers is ω=$10, half the assumed size of the LS farmers'. Again we find that when ρ = 0.4 for LS farmers, for example, there is no level of BMPC risk aversion at which BMPC farmers would have an equal or lower discount rate than the LS farmers.

We present these results on background consumption only because background consumption shows up in the model and therefore presents an opening for questions about its role. Our preliminary analysis suggests its role is likely to be minor. Further analysis is needed to explore any empirical role, however; unlike risk aversion and consumption smoothing, background consumption can be measured with reasonable accuracy. The interpretation of background consumption's role, if such a role were found, is considerably more complex than risk aversion, since consumption may be correlated both with individual preferences and with investment opportunities.

6. Discussion and Conclusion

This paper estimates the difference in the average discount rates of two groups of farmers that are known to be early or late adopters of farm management technologies. We find that early adopters have much lower risk-neutral discount rates than late adopters. We further find that this difference is due to greater impatient and not to higher risk aversion. Even with levels of consumption smoothing set to one-tenth of the optimal levels, our findings suggest that risk aversion levels would have to be untenably large for greater risk aversion, rather than greater impatience, to explain the difference between BMPC and LS farmers.

Our results are consistent with the hypothesis that individuals with high discount rates will be less likely to adopt beneficial technologies. For farmers, this means that innovations in seed variety, precision agriculture, and conservation methods may not result in widespread adoption even if the net benefits of the technology (calculated at market interest rates) are positive. Adoption among farmers with high discount rates may only occur slowly with further adjustments in the market such as an increase in the price of existing technology (as the supply of older technology decreases) or with further decreases in the price of the new technology. Therefore, understanding how discount rates vary in the population is likely to be helpful in understanding how to overcome low levels of adoption of socially desirable technologies and programs.

Difference in discount rates could also affect the performance of policies designed to encourage farmers to adopt environmentally-friendly practices, including the Best Management Practices that are the focus of this article. These policies typically provide incentive payments and cost-sharing for farmers. This paper's results suggest that the timing of these payments could be used to make such programs more attractive to different subsets of farmers.

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