Subprime Consumer Credit Demand: Evidence from a Lender's Pricing Experiment

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Using a unique panel data set from a U.K. credit card company, we analyze the interest rate sensitivity of subprime credit card borrowers. In addition to all individual transactions and loan terms, we have access to details of a randomized interest rate experiment conducted by the lender on existing (inframarginal) loans. For the whole sample, we estimate a statistically significant £3.4 reduction in monthly credit demand in response to a five percentage point increase in interest rates. This aggregate response is small, but it masks very interesting heterogeneity in the sample. We find that only low-risk borrowers who fully utilize their credit cards lower their credit demand significantly when faced with an increase in interest rates. We also document that a five percentage point increase in interest rates generates significant additional revenue for the lender without inducing delinquency over a short horizon. (*JEL* D11, D12, D14)

Borrowing rates affect firms' and households' demand for credit. Quantifying such effects, that is estimating credit demand elasticities, has become an increasingly important academic endeavour. At the microlevel, lenders are interested in gauging these elasticities as an input to their optimal loan pricing strategies. At the macrolevel, knowledge of these elasticities is essential for understanding the transmission of monetary policy. Moreover, they can be

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informative about whether households are credit constrained or whether they borrow responsibly and understand the basic credit terms offered to them. The latter point is particularly important because recent research documents low debt literacy and high financial vulnerability among a large number of households (see Lusardi and Tufano 2009). Such households are the primary concern of this paper.

We estimate the sensitivity of credit demand to a large interest rate hike for individuals who are deemed to be *subprime* borrowers. We do this using a unique panel data set on credit card transactions from a private lender. Our lender serves only the subprime market in the United Kingdom.[1] The strength of the paper relative to previous related studies is that we have access to a large *exogenous* change in interest rates. This variation is generated by the lender's *randomized price* experiment. To conduct the experiment, the lender classifies clients according to a behavior score that is designed to measure a client's riskness (low, medium, or high) and their utilization of credit cards (low, medium, or high). This 3×3 classification produces nine "cells," and in five of these, the lender conducts a randomized experiment with a five percentage point interest rate increase. This setting not only allows us to identify the causal effect of borrowing costs on credit demand for inframarginal loans but also gives us the opportunity to assess heterogeneity in treatment effects.

Subprime borrowers are commonly presumed to be credit constrained, implying that they will not reduce borrowing in response to an interest rate increase. This argument lends itself to the conclusion that the interest rate increase necessarily leads to higher interest charges (revenue) for the lender and a faster debt accumulation for the borrowers. For the whole sample, we estimate a statistically significant £3.4 reduction in monthly credit demand in response to a five percentage point increase in interest rates. This aggregate response is small. We find no effect of the interest rate increase on the short-run probability of a client becoming delinquent. Together, the small reduction in monthly credit demand and the lack of an increase in delinquencies mean that the interest rate increase does lead to higher interest charges for the lender and no reduction in the stock of debt for the borrowers. The finding that there is no reduction in debt despite the reduction in monthly credit demand is due to the fact that the increased interest rate applies to the entire stock of accumulated debt.

This overall picture does, however, mask some important heterogeneity in the sample. We find credit demand reductions that are neither statistically nor economically different from zero among borrowers with high utilization rates and medium to high default risk. This is consistent with these particular borrowers being credit constrained. On the other hand, we estimate a

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[1] For confidentiality reasons, we do not disclose the name of the company. We will refer to it hereafter as the "lender."

statistically significant £9.0 reduction in monthly credit demand for borrowers with high utilization rates and low default risk. However, even for this group, the response to the interest rate increase is not strong enough to lower the interest charges. In fact, despite their efforts, treated individuals in this group pay a 10% higher interest charges relative to controls.

Borrowers with moderate utilization rate and "low default risk" also exhibit no sensitivity to higher interest rates. This is at first sight surprising because the unused borrowing capacity of individuals in this group suggests they are not credit constrained. These borrowers, however, had an increase in their credit limit just prior to the experiment. This increase makes them appear to be borrowers who do not fully utilize their credit cards. Hence, a potential interpretation of their behavior might be that the increase in credit limit relaxed their previously binding credit constraint. Their insensitivity to the interest rate increase directly translates into a significant debt accumulation (£71, corresponding with a 8.5% increase in total debt outstanding relative to the control) over three months following the interest rate increase.

Estimating interest rate sensitivity of credit demand using survey data has been challenging for researchers. This is because the cross-sectional variation in interest rates is likely to be endogenous to borrowing and repayment behaviors through unobservable characteristics of the borrowers. Previous studies tried to overcome this challenge by using quasiexperimental designs.[2] However, these research designs require strong identification assumptions. The experimental setting of our data gives us clean identification of credit demand elasticities without resorting to such assumptions.[3] Moreover, the interest rate increase in our data is substantial (five percentage points) and the experimental sample size is large enough that we can be confident of detecting any economically significant effects.

Our study concerns a subset of households in a developed economy that are considered to be financially vulnerable. The U.K. credit market is a highly sophisticated market in which lenders have access to advanced risk pricing technologies. Such an environment allows access to formal credit (albeit at a high price) for households who would otherwise be rationed out. This access can provide insurance to temporary disruptions in households' income (such as

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2 Attanasio, Goldberg, and Kyriazidou (2008) estimate interest rate elasticities of car loan demand by exploiting the tax reform of 1986 in the United States. Alessie, Hochguertel, and Weber (2005) analyze the same issue using a similar design. Gross and Souleles (2002) use the U.S. Credit Bureau data and propose some firm-specific practices as instruments for borrowing rates. Adams, Einav, and Levin (2009) use data on a U.S. private subprime auto loan company. The general conclusion drawn from the studies is that there seems to be no sensitivity to borrowing rates among low-income households. However, such households display some sensitivity to loan features related to liquidity, such as down payment requirements, credit limits, and loan maturities. This finding is interpreted as the presence of binding liquidity constraints. The exception is the Gross and Souleles (2002) study in which the authors find evidence of significant elasticity of credit card debt with respect to interest rates.

3 Examples of identification assumptions include general exclusion restrictions for IV methods and common trend assumptions for difference-in-differences methods.

unemployment and sickness) and therefore can be beneficial.[4] However, access to high cost credit can pose a danger for financially fragile households if they borrow too much, relative to their means. The evidence reported in this paper provides novel insights on (1) the prevalence of liquidity constraints and (2) the mechanism of debt accumulation among subprime borrowers in developed economies. Such insights are critical to the development of public policy and consumer protection actions targeting financially vulnerable households in the United Kingdom and other developed economies.[5]

From a policy point of view, the results illustrate (1) the vulnerability of subprime borrowers to interest rate increases and (2) that interest rate increases would be profitable for the lender for almost all types of borrowers studied.[6] Whereas imposing interest rate caps might be an unpalatable option for a policy maker (because it could result in credit rationing), a range of other policy interventions might aid these individuals. These include restrictions on credit limit increases (particularly, limit increases initiated solely by the lender) and higher required minimum payments. A policy that requires lenders to fully explain and illustrate the consequences of higher interest rates on debt accumulation might also be beneficial.

The rest of the paper is organized as follows. We provide a brief overview of the U.K. credit card market in the next section. In Section 2, we present our data and the experimental design. In Section 3, we motivate our outcome variable and assess the magnitude of expected response to the experiment. We present and discuss the results in Section 4, and Section 5 concludes.

1. Subprime Credit Card Market in the United Kingdom

Credit cards have steadily grown in importance as a payment device in all industrialized countries. As of 2007, it is estimated that approximately 70 million credit cards were in issue in the United Kingdom. These cards were responsible for 22.4% of the total consumer transactions, which stood at £540 billion in 2007 (see Data monitor 2008). Moreover, borrowing on credit cards (revolving credit card debt from one month to the next and therefore incurring interest charges) has grown rapidly over the last few decades in the

[4] Karlan and Zinman (2010) show that access to consumer credit even at very high rates can be beneficial. The randomly assigned marginal loans produced significant net benefits for borrowers across a wide range of outcomes in South Africa.

[5] The evidence on the credit elasticities of financially vulnarable households is limited, but there is a large body of academic literature on estimating credit elasticities in developing countries. Using a field experiement, Karlan and Zinman (2008) and, using between-branch variation, Dehejia, Montgomery, and Morduch (2012) provide evidence on the size of credit demand elasticities in South Africa and Bangladesh, respectively. Karlan and Zinman (2008) estimates modest interest rate sensitivity of the demand for new term loans in South Africa, with demand apparently more sensitive to loan maturity. Dehejia, Montgomery, and Morduch (2012) estimate subtantial interest rate sensitivity among the poor.

[6] A caveat applies to this result as the implications of the lender's profitability are based on short-run estimates. It is plausible that a permanent increase in interest rates has different long-run consequences, such as default or driving away clients.

United Kingdom attracting much attention from consumer protection groups, regulatory bodies, and, of course, the media. In 2007, total credit card debt stood at around £65 billion, representing approximately 30% of consumer credit in the United Kingdom.

Consumers who are not considered suitable for unsecured credit by mainstream issuers comprise the U.K. nonstandard credit card market. The term "subprime" refers to a subsection of the nonstandard market in the United Kingdom. This subsection usually consists of individuals with adverse credit histories, that is, individuals with an even higher risk of default than the typical nonstandard individual. Individuals deemed to be subprime borrowers are more difficult to evaluate in terms of default risk. This can be because of volatile income (e.g, many in this category are self-employed), low income (e.g., unemployment), lack of credit history in the United Kingdom, or impaired credit history due to past defaults or mortgage arrears.[7] Therefore, lenders targeting this segment (such as our lender) invest heavily in advanced risk pricing technologies to combat the adverse effect of delinquencies and defaults. The lender's randomized price experiments are part of its risk pricing practice.

2. Data and Experimental Design

Our data set is provided to us by a private credit card issuer, who is one of the major players in the subprime segment of the U.K. market. The data set comprises all individual transactions, including purchases, cash advances, payments, interest charges, and fees. We also have income, age, marital status, and home ownership reported by individuals at the application stage.

Our lender has routinely performed randomized interest rate experiments on subsamples of clients since 2006. The main reason for these experiments is to establish sensitivity to interest rates as part of the company's risk pricing practice. Each experiment lasted between 3–6 months, and the lender initiated another experiment immediately following the previous one. Interest rate changes were permanent until the next change took effect. All interest rate experiments were designed based on ex-ante-determined blocks, which we will explain in greater detail later. The lender agreed to provide us with two of the experiments, called Phase 2 and Phase 6. As the later experiment, Phase 6, involved a much larger number of individuals and a much higher intensity of treatment (five percentage point increase in interest rates for all treated individuals), we chose to use these data. The experiment involved 39,883 individuals. The randomization was done in November 2007, and the interest rate changes were communicated to the individuals allocated to treatment groups in January 2008. The interest rate changes were implemented

[7] The main reason to fall into the subprime catagory is a County Court Judgement (CCJ) record. County Court Judgement refers to an adverse ruling of the County Court against a person who has not satisfied debt payments with their creditors. An adverse ruling remains on the individual's record for six years from the date of judgement.

Table 1
Descriptive statistics

	Mean	Median	SD
Utilization rate (%)	79.4	94.8	33.4
Statement balance (£)	848.7	726.6	633.4
Debt (£)	743.2	628.5	615.6
New transactions (£)	76.1	0.0	182.4
Credit limit (£)	1,182	1,000	796.8
Interest rate (%)	30.9	30.0	2.3
Income (£)	17,866	15,500	15,910
Age	42.1	41.0	11.8
Married (%)	56	–	–
Employed (%)	63	–	–
Self employed (%)	10	–	–
Home owner (%)	34	–	–
No other card (%)	42	–	–

The table presents the descriptive statistics of the individuals in the sample at the time of the randomization (November 2007). The total number of individuals is 39,883. Variables include utilization rate, statement balance, outstanding credit card debt, new transactions, credit limit, interest rates, self-reported income, and age. The table also reports the composition of the sample in terms of marital and employment status, home ownership, and ownership of other credit cards.

in February 2008. We have data until May 2008, so we can measure the effect of interest rate changes over the three months following the implementation, that is, from February to April 2008. We lose one month because of lagging for the construction of our outcome variables.

The experimental sample was not chosen from the lender's full client base. Accounts that are flagged for reasons such as default, several months of delinquency, or inactivity are excluded before the selection of the sample. Furthermore, the lender excluded individuals who have been with the lender for less than seven months at the time of the design. Table 1 presents the characteristics of the individuals in the sample at the time of the randomization (November 2007).

The median income reported at the time of application is £15,500. Given that the median individual income for the United Kingdom is about £19,000, individuals in our sample represent the lower end of the income distribution. The average monthly utilization rate, defined as outstanding monthly balance divided by the credit limit, is about 79.4% with the median value of 94.8%. The average utilization rate for all U.K. credit card borrowers is approximately 34% (see the Data monitor [2008] report). Interest rates and credit limits are the two other variables highlighting the differences between our average borrower versus the average U.K. borrower. The mean (median) interest rate is 30.9% pa (30.0% pa). These interest rates are significantly higher than the rates on typical U.K. credit cards (approximately 15%–18% pa). The mean (median) credit limit is £1,082 (£1,000), which is much lower than the average U.K. credit card limit of £5,129 in 2007.

As Table 1 shows, the average monthly purchase value is about £76 with the median value of £0. It is worth drawing attention to the size of revolving debt in the table. This figure is calculated as the balance appearing on the

November 2007 statement minus the payments made toward that balance in the following month (December 2007). This is the debt revolved from November to December, to which the interest charge is applied. The mean revolving debt in November 2007 is approximately £743, with the median value of £628. This is quite a large figure given a monthly interest rate of about 2.5%. It is clear that a significant portion of the individuals in our data set use their card for borrowing purposes. To be precise, approximately 81% of the individuals in our sample revolved debt every month between November 2007 and April 2008.

2.1 Experimental design

Perhaps the most intriguing feature of our data is that the lender had changed its clients' interest rates through randomized trials since 2006. They carried out the randomization as a block design in which a sample of individuals were assigned to blocks (cells, henceforth) defined by the interaction of utilization rates and an internally developed behavior score that summarizes individuals' risk characteristics.[8] Individuals were allocated into cells according to their utilization rates and behavioral scores as of November 2007. After the allocation, the randomization was performed within cells. Such designs are well known in the statistical, medical, and experimental economics literatures. Simple randomization to treatment and controls is rarely employed in real randomized control trials for a number of reasons. For example, block designs reduce the variance of the experimental estimates (see, e.g., List, Sadoff, and Wagner [2011] or Duflo, Glennerster, and Kremer [2006]). This design implies that within cells, there is no selection problem, and conditional on cells, interest rate changes are exogenous.

Table 2 presents the cell design, the sample sizes of each cell, and the number of individuals allocated into the treatment and control groups. In each cell, individuals in the treatment group (approximately 93.5% of the individuals) received a five percentage point increase in interest rates. For example, cell 1 contains individuals who had high utilization rates and low behavior scores (high default risk) in November 2007. In this cell, 4,319 individuals were allocated in the treatment group, whereas 280 individuals were in the control group. Similarly, cell 9 contains individuals who had low utilization rates and high behavior score (low default risk). In this cell, 4,030 individuals received a five percentage point increase in interest rates, whereas 276 individuals were in the control group. Note that the control size is quite small. However, as we show and discuss in the results section, these data give us a reasonable statistical power to estimate the economically significant impact. Note also that a 50/50 allocation to treatment and control is not necessary and in general not optimal (see List, Sadoff, and Wagner 2011). For cells 2, 3, 5, and 6, the lender did

[8] Internally developed credit scoring systems are general practice for credit card issuers. We do not know the exact features of our lender's scoring system, but we were informed that it is a continously updated, multivariate-probit-type algorithm.

Table 2
Descriptive statistics

Utilization Rate (100%)	Low	Mid	High
High	**CELL 1** T=5pp #T=4319 #C=280	**CELL 4** T=5pp #T=8,072 #C=573	**CELL 7** T=5pp #T=14,418 #C=995
Mid	**CELL 2** T=5pp #T=281 #C=0	**CELL 5** T=5pp #T=3,252 #C=0	**CELL 8** T=5pp #T=6469 #C=451
Low	**CELL 3** T=5pp #T=137 #C=0	**CELL 6** T=5pp #T=1,065 #C=0	**CELL 9** T=5pp #T=4,030 #C=276
0	Behavior Score (Bscore)		

The matrix presents the cell design of the experiment, the sample sizes of each cell, and the number of individuals allocated into the treatment (T) and control (C) groups. The lender classifies individuals according to a behavior score (Bscore) that is designed to measure the client's riskiness (low, medium, or high) and their utilization of credit cards (low, medium,or high). In each cell, individuals in the treatment group (approximately 93.5% of the individuals) received a five percentage point increase in interest rates (T=5pp).

not allocate individuals to a control group, making them unavailable for our purposes.

2.2 Implementation

Unlike studies using randomized field experiments (mainly in development economics), we were not involved in the design or implementation of the experiment on which our analysis is based. Although randomized experiments are now standard practice among credit card companies and they have every incentive to implement them correctly, we need to make sure that the randomization was carried out properly to ensure the internal validity of our results.

We perform mean equality tests on a range of variables including, our outcome variable. These tests are carried out using the variables measured in November 2007 (the date of the randomization). Table 3 presents the means of tested variables for the treated and control. The p-values obtained from mean equality tests are displayed in parentheses. As shown in the table, we could not detect any statistically significant difference between the treated and control groups in any cell (as would be expected when randomization is carried out correctly).

Even though the randomization was carried out properly, there may be other challenges to the internal validity of our experimental estimates. Sample attrition, for example, would be of particular concern if it were caused by the treatment. This could happen if the treatment initiated delinquency and eventually default, making the remaining treatment sample no longer comparable to the control sample (a dynamic selection problem). If the treatment caused some accounts to be charged off, our treatment effect estimates may be biased toward finding insensitivity to interest rates. Alternatively, if the

Table 3
Internal validity checks

Variable	Cell 1 T	Cell 1 C	Cell 4 T	Cell 4 C	Cell 7 T	Cell 7 C	Cell 8 T	Cell 8 C	Cell 9 T	Cell 9 C
Utilization %	104	105	97.9	98.1	94.5	94.5	50.9	50.7	5.06	5.40
	(0.24)		(0.18)		(0.98)		(0.77)		(0.52)	
Bscore	585	586	681	682	717	717	726	726	740	739
	(0.92)		(0.54)		(0.63)		(0.85)		(0.15)	
Debt (£)	784	782	787	787	1,015	1,018	656	667	42.3	40.7
	(0.96)		(0.99)		(0.88)		(0.64)		(0.88)	
Credit limit (£)	811	799	867	876	1,172	1,179	1,555	1,548	1,663	1,642
	(0.72)		(0.69)		(0.75)		(0.86)		(0.73)	
New transactions (£)	16.7	12.2	36.2	38.1	86.1	90.6	153.1	153.4	62.5	60.2
	(0.18)		(0.78)		(0.44)		(0.98)		(0.80)	
Interest rates %	31.3	31.4	31.4	31.3	30.7	30.8	30.8	30.9	30.2	30.3
	(0.55)		(0.77)		(0.20)		(0.26)		(0.64)	
Interest charges (£)	20.2	20.0	21.0	21.0	25.7	25.6	17.2	17.2	5.4	4.4
	(0.76)		(0.99)		(0.94)		(0.97)		(0.09)	
Income (£)	17,678	17,929	17,543	17,089	17,794	17,105	18,071	17,241	18,694	18,163
	(0.82)		(0.44)		(0.24)		(0.18)		(0.68)	
Net new B. (£)	−25.1	−24.0	−19.9	−23.1	3.78	5.20	45.5	52.0	7.01	4.64
	(0.24)		(0.49)		(0.50)		(0.40)		(0.80)	

The table shows the mean values for treatment and control for our variables of interest and control variables in the month of randomization (November 2007). T, treatment; C, control. P-values for equality tests are in parentheses.

treatment caused voluntary closures of accounts, our treatment effect estimates may be biased toward finding sensitivity. With respect to the latter, we find that no account was closed within the sample period. For the former, recall that we can follow outcomes of the experiment only for three months. It is unlikely that we would see any default in such a short period, as it takes six months for the lender to charge off the delinquent account. The lender stops charging interest on the outstanding debt after four months of delinquency (by law). The defaulted debt is transferred to the collection agency after six months.

However, we can explore whether the treatment induced intention to default by looking into the number of delinquent months following the treatment. If the treatment induces default, we may observe it as delinquency (missed monthly payments), beginning with the date the interest rate increase was communicated (January 2008). For this, we investigate whether there is any statistically significant difference between the treated and control groups in terms of falling into a delinquency cycle after the communication of the interest rate increase. We do not reject the hypothesis of equality and conclude that the treatment did not induce delinquency within the sample period.[9] We will return to the implications of this issue later in the text.

[9] Another problem common in randomized experiments is noncompliance, that is, the possibility that units allocated to the treatment group are not treated. This situation could arise in our case if, for example, some individuals that are allocated to a treatment group objected to the interest rate increase and the lender consequently reversed the change. Fortunately, we do not face this problem in our sample; all accounts that are allocated into treatment groups did receive the change in interest rates.

3. Outcome Variable and Expected Effects

We begin our analysis by first characterizing our borrowers using a standard intertemporal consumption framework. We do this to motivate our outcome variable and to generate testable hypotheses. To this end, we argue that individuals in our data set are very likely to be net borrowers. A net borrower who is not liquidity constrained is expected to lower his credit demand (his consumption) when faced with an increase in borrowing rate, because this increase implies an increase in the price of today's consumption (a substitution effect). The subsequent decline in consumption is reinforced by the fact that the individual is now lifetime poorer as he carries forward a stock of debt (an income effect). On the other hand, a borrower who is constrained by his credit limit is not likely to change his consumption following a (small) interest rate change but he may react to large changes.[10]

In this section, we outline our measure of credit card borrowing. We then address the following question: What should be the expected response of an individual in our sample when faced with a five percentage point increase in his borrowing rate? An important feature of credit card debt is that changes in interest rates apply to the existing stock of debt. Hence, when faced with an increase in interest rate, the individual's debt automatically increases due to the additional interest charges. For this reason, we cannot use the stock of credit card debt as a choice variable. The actual monthly credit demand for a credit card user is monthly purchases on credit minus the subsequent payments made toward the outstanding balance. This difference constitutes the monthly addition to the existing credit card debt that accrues interest; thus, it forms our outcome variable. We call our outcome variable "net new borrowing," *NNB*, and we define it as

$$NNB_{t+1} = NT_{t,t+1} - P_{t+1}, \tag{1}$$

where $NT_{t,t+1}$ is new transactions made on credit between month t and $t+1$, and P_{t+1} is the payment made toward the outstanding balance at $t+1$. $NT_{t,t+1}$ is interest exempt between period t and $t+1$,[11] whereas if $NT_{t,t+1} - P_{t+1} > 0$, the difference accrues interest charges until paid. Therefore, a positive (negative) value for *NNB* indicates an increase (decrease) in monthly credit demand. We expect the unconstrained borrower to reduce *NNB* when faced with an increase in borrowing rates.[12]

[10] Note that the latter prediction refers to the strongest definition of liquidity constraints for which there is an actual quantity limit to borrowing. One can also extend the notion of liquidity constraint to individuals who face increasing borrowing cost with quantity demanded as in Pissarides (1978).

[11] This is not the case for cash advances that are included in *NT*, in which case the interest charges resume as soon as the cash advance is made.

[12] For most credit card products, monthly payment P_{t+1} is subject to

$$P_{t+1} \geq Max[\kappa B_t, \theta],$$

How large do we expect the reduction in borrowing to be? To answer this question, we postulate that the individual is a lifetime utility maximizer with a time-separable utility function. We further assume that the only tool available to him to implement his desired consumption profile is credit card borrowing. For such an individual, monthly consumption $C_{t,t+1}$ between month t and $t+1$ can be described as

$$C_{t,t+1} = Y_t + NNB_{t+1}, \tag{2}$$

where Y_t is the individual's income at t. The magnitude of reduction in consumption (due to the reduction in *NNB*) depends on the elasticity of intertemporal substitution, which is a structural parameter that measures the sensitivity of consumption to interest rates. To be sure that the experiment we study has the statistical power to reject our hypotheses, we calculate expected economic effects (expected reduction in *NNB*) assuming that the individual has a constant relative risk aversion (CRRA) utility function:

$$U(C) = \frac{C^{1-\gamma}}{1-\gamma}, \tag{3}$$

where γ is the coefficient of relative risk aversion, and its reciprocal $(\frac{1}{\gamma})$ measures the elasticity of intertemporal substitution.

Given the CRRA utility function, the first-order condition of the maximization problem of a lifetime utility maximizer can be written as[13]

$$C_t^{-\gamma} = \frac{(1+r_{t+1})}{(1+\delta)} E_t\left[C_{t+1}^{-\gamma}\right], \tag{4}$$

where $E_t[C_{t+1}^{-\gamma}]$ is the expected marginal utility of consumption for $t+1$; r_{t+1} is the borrowing rate between t and $t+1$; and δ is the subjective discount rate. Equation (4) states that the lifetime utility maximizing individual must make the marginal utilities equal across time. This equation, known as the Euler Equation, has been the workhorse of empirical macroeconomics since Hall (1978). Taking the logarithm of both sides and differentiating it with respect to $\ln(1+r_{t+1})$ we obtain

$$d\ln C_t = -\frac{1}{\gamma}\left[1 + \frac{\partial \ln E_t\left[C_{t+1}^{-\gamma}\right]}{\partial \ln(1+r_{t+1})}\right] d\ln(1+r_{t+1}). \tag{5}$$

The above equation states that a change in interest rates will generate a substitution effect (first term), which is unambiguously negative, and an income

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where B_t is the statement balance (interest accrued debt plus new transactions), κ is the fraction used to calculate required minimum payment, and θ is a known amount to be paid if $\kappa B_t < \theta$.
Note, however, that the payment variable can be decomposed as

$$P_{t+1} = Max[\kappa B_t, \theta] + DP_{t+1},$$

where κB_t is the required minimum payment that is determined by the statement balance (and therefore interest rate sensitive), and DP_{t+1} is the "discretionary payment" made over and above the minimum payment required.

13 See the Appendix for the details of the derivations in this section.

effect (second term). For an individual with outstanding credit card debt, an increase in borrowing rates will lower future consumption (i.e., increase the future marginal utility of consumption, implying a negative income effect) so that

$$\frac{\partial \ln E_t\left[C_{t+1}^{-\gamma}\right]}{\partial \ln(1+r_{t+1})} > 0. \tag{6}$$

Unfortunately, we cannot calculate the income effect, but we can calculate the substitution effect for a given value of γ, which is $(-\frac{1}{\gamma}d\ln(1+r_{t+1}))$. Note that the substitution effect will give us the lower bound for the reduction in consumption so that

$$|\Delta \ln C_t| > \left|\frac{1}{\gamma}\Delta \ln(1+r_{t+1})\right|. \tag{7}$$

In words, the impact on consumption must be at least the substitution effect for a net borrower. For example, for a borrower with an annual average consumption of £16,000, an elasticity of intertemporal substitution of $\frac{1}{\gamma} = .50$, and an interest rate of 30% pa, we expect a reduction of £25 in monthly consumption in response to a five percentage point increase in interest rates.[14] Note that the above relationship is true even if the borrower also holds savings, as long as saving and borrowing rates are different. An increase in borrowing rates (without any change in saving rates) still implies a negative income and substitution effect. We expect the borrower who also holds assets to pay down his debt by liquidating his assets in response to an increase in borrowing rates.

What is the plausible value for γ? Both the micro- and macroliterature provide evidence on the magnitude of the elasticity of intertemporal substitution (see Attanasio et al. 1999; Gourinchas and Parker 2002; Andersen et al. 2008; Alan and Browning 2010). Rather than subscribing to a particular value, we calculate the lower bound for γ, below which our experimental design has sufficient power to reject a null of no response with 80% confidence. We clarify this point further when we discuss our results in the next section.

4. Results

4.1 Experimental estimates

As outlined in the previous section, we use the net new borrowing of the individual to estimate the sensitivity of credit demand to interest rates:

$$NNB_{i,t,j} = \alpha_j + \beta_j TR_i + \boldsymbol{\theta}'_j \mathbf{X}_{i,j} + \varepsilon_{i,t,j} \quad j = 1,4,7,8,9, \tag{8}$$

where $NNB_{i,t,j}$ denotes the net new borrowing of individual i at time t in cell j.

[14] Given these values, $\frac{1}{\gamma}\Delta\ln(1+r_{t+1})16,000 = 0.5[\ln(1.35) - \ln(1.30)]16,000 = £302$, expected change in monthly consumption is at least $302/12 = £25$.

TR_i is a treatment dummy that takes the value of one if individual i is in the treatment group and is zero if the individual is in the control group. The fact that the randomization was carried out properly assures us that there should be no difference between the treatment and control groups other than receiving the treatment. Then the coefficient β_j in the above regression gives us an unbiased estimate of the *average* treatment effect (ATE) for cell j, that is,

$$\beta_j = E\left(NNB_{i,t,j} \middle| TR_i = 1\right) - E\left(NNB_{i,t,j} \middle| TR_i = 0\right) \quad j = 1,4,7,8,9. \tag{9}$$

The control variables in $\mathbf{X}$ include pretreatment interest rates, income, age, marital status, and employment status, which are independent of the treatment status. They are included only to increase the precision of the estimated treatment effects by reducing the variance of ε. The estimated average treatment effect for the whole sample is the weighted average of the cell-by-cell ATEs. Following standard practice, we correct the standard errors to take into account the panel structure (autocorrelated errors) and the possibility of heterogenous treatment effects (heteroscedasticity).

For current liquidity-constrained individuals, the estimated average treatment effect β is expected to not be statistically different from zero. In our data set, those individuals are likely to be those with high utilization rates (cells 1, 4, and 7). Borrowers with low utilization rates are expected to lower their consumption (equivalent to lowering *NNB* in this framework) when faced with an increase in interest rates. This is because they do have available borrowing opportunities, but they choose not to fully utilize them (they could borrow more on this card). Cells 8 and 9 fit this description. The mean utilization rate is approximately 50% for cell 8 and around 10% for cell 9 in November 2007.

Table 4 presents the results. The second column of the table presents average treatment effects (β), whereas the first column presents the controls' mean *NNB*. The third column presents the absolute minimum detectable effects. These values are the minimum true differences (in British pounds) between the control and treated groups that can be statistically detectable with 80% confidence at a 5% significance level (see List, Sadoff, and Wagner 2011). Put differently, the minimum detectable effect tells us *how wrong* the null (null of "no response") must be to be rejected with an 80% confidence in repeated samples. The last column reports the maximum value the coefficient of relative risk aversion γ can take so that the response to this treatment by an unconstrained borrower would exceed the minimum detectable effect. For example, in cell 1, we can detect an economic impact as low as £9.2 if the coefficient of relative risk aversion is less than 5.34. The estimates of the microliterature on γ range from 0.5 to 3 (Attanasio et al. [1999] estimates it around 1.5, Gourinchas and Parker [2002] between 0.5 to 2, and Andersen et al. [2008] around 0.7). The macroestimates, using aggregate data, appear to be smaller, around 1 (Guvenen 2006). Given these estimates, we are confident that our experiment has sufficient statistical power to detect any economically significant impact.

Table 4
Experimental estimates

Average treatment effects (β): $NNB_{i,t,j} = \alpha_j + \beta_j TR_i + \boldsymbol{\theta}'_j \mathbf{X}_{i,j} + \varepsilon_{i,t,j}$

Cells	Control's *NNB*	Average treatment effect β	Abs. min. det. effect	EMEE > AMDE
Cell 1	−20.0** (3.55)	−1.74 (3.68)	9.2	$\gamma < 5.34$
Cell 4	−24.1** (2.80)	−1.28 (2.92)	7.3	$\gamma < 6.72$
Cell 7	−21.5** (3.04)	−9.04** (3.15)	7.8	$\gamma < 6.29$
Cell 8	4.21 (6.49)	8.20 (6.61)	16.6	$\gamma < 2.96$
Cell 9	39.4** (7.62)	−8.03 (7.80)	19.0	$\gamma < 2.58$
Whole sample	−12.4** (2.04)	−3.42* (2.03)	5.0	$\gamma < 9.82$
Excluding cell 8	−14.1** (2.00)	−4.83** (1.67)	4.2	$\gamma < 11.7$

The dependent variable $NNB_{i,t,j}$ is the monthly net new borrowing of individual i in cell j. The control variables include income, marital status, employment status, home ownership, and pretreatment interest rates. Clustered standard errors are in parentheses. The last column presents the values of the coefficient of relative risk aversion γ below which the experimental data do have the statistical power to detect the minimum detectable effect. They are found by setting $\frac{1}{\gamma}\Delta \ln(1+r_{t+1}) * MedianIncome = MDE$ and solving for γ for each cell. They are calculated at the pretreatment median interest rates (29.95%) and monthly median income of £1,300 (proxy for monthly consumption) in this sample. EMEE, expected minimum economic effect; AMDE, absolute minimum detectable effect. Minimum detectable effects: 80% statistical power, 5% significance. All values in the first three columns are in British pounds (£).

Contrary to our priors, only in cell 7 (high utilization, low default risk group) do we estimate a statistically significant reduction in credit demand. This group lowered its monthly credit demand by about £9 when faced with a five percentage point increase in interest rates (the control group's mean is £21.5). We do not see a reduction in credit demand in other high utilization cells. The point estimates for cells 1 and 4 are very small (less than £2 for each), and they are statistically insignificant. The significant reduction in net new borrowing in cell 7 indicates that this group may have other borrowing opportunities, so they are not constrained by their credit limits.

Our striking result comes from borrowers in cells 8 and 9, those with low utilization rates and low default risk. These are individuals for whom we expect a significant reduction in credit demand because they do have spare capacity for borrowing that they have not yet used. However, as can be seen in Table 4, the estimated average treatment effect for these cells is not statistically different from zero. We see no evidence of a reduction in credit demand for these cells: Although the point estimate for cell 9 has the expected sign (−£8.03), it is not statistically significant.

When we pool all the cells together we find that there is a small reduction of about £3.4 in monthly credit demand. This estimate is significant at the 10% level. However, the estimated effect for the sample becomes larger and statistically more significant if we exclude cell 8. We find a £4.8 reduction in monthly credit demand for our sample, excluding cell 8. We will discuss the peculiarities of this cell in the next subsection.

We repeat our empirical analysis using the outcome variable "discretionary net new borrowing," *DNNB*. We define *DNNB* as

$$DNNB_{t+1} = NT_{t,t+1} - DP_{t+1}, \tag{10}$$

where DP_{t+1} is the "discretionary payment" made over and above the minimum payment required. "Discretionary net new borrowing" is purged of the purely mechanical increase in required minimum payments that is associated with an increase in interest rate and consequently in outstanding debt.

With the new outcome variable we still confirm the interest rate sensitivity finding in cell 7 and no sensitivity in any other cell. We also split the sample based on home ownership, income, and having another credit card to see whether the sensitivity documented in cell 7 comes from relatively wealthier borrowers with other means to smooth consumption. The results we obtain for cell 7 are remarkably robust to splitting the sample by income (less than £10,000 versus more than £10,000), based on having another credit card and based on home ownership. We find evidence of a reduction in credit demand in all subcells of cell 7. At the same time, the insensitivity results in other cells carry through, even when we split the cells by income, home ownership, and the presence of another card.[15]

4.2 Implications for the borrower: Total credit card debt

We now turn to examine how the stock of debt is affected by the interest rate hike over the three-month period. For this, we estimate the average treatment effect on the three-month change in the stock of credit card debt from February 2008 to April 2008 for each cell, that is,

$$\Delta D_{i,j} = \alpha_j + \beta_j TR_i + \boldsymbol{\theta}'_j \mathbf{X}_{i,j} + \varepsilon_{i,j} \quad j = 1,4,7,8,9, \tag{11}$$

where $\Delta D_{i,j} = Debt_{i,j}^{April} - Debt_{i,j}^{Feb}$ for individual i in cell j. Recall also that we define $Debt_{i,j}^{April} = Balance_{i,j}^{April} - Payment_{i,j}^{May}$ and $Debt_{i,j}^{Feb} = Balance_{i,j}^{Feb} - Payment_{i,j}^{March}$.

Table 5 presents the estimates. Consistent with our previous results on net new borrowing, we estimate a decline in debt for cell 7 over the three-month period. The change in debt caused by the treatment is estimated to be −£19.3, but the estimate is statistically not different from zero. Despite the reduction in net new borrowing, this group cannot lower the stock of debt significantly. We find a statistically significant increase in debt for cell 8 (about £71) over the three-months following the treatment. This corresponds with an 8.5% higher stock of debt relative to the control in the month of April for this cell (the average stock of debt for the control group stands at £817.5 in April 2008 for cell 8). We observe no statistically significant change in debt within the three-month period in any other cell. The point estimate for cell 9 is quite high but it

[15] Results available upon request.

Table 5
Experimental estimates

Average treatment effects for 3-month debt accumulation
$\Delta D_{i,j} = \alpha_j + \beta_j TR_i + \theta'_j \mathbf{X}_{i,j} + \varepsilon_{i,j}$

Cells	Control's ΔD	ATE ΔD
Cell 1	11.8 (20.1)	−6.12 (16.8)
Cell 4	30.6* (15.4)	−.50 (11.3)
Cell 7	61.8** (19.2)	−19.3 (13.7)
Cell 8	35.9 (36.3)	71.1** (28.1)
Cell 9	198** (43.1)	−61.9 (39.6)
Whole sample	65.3** (8.7)	−2.65 (8.94)
Excluding cell 8	66.5** (8.9)	−15.0** (7.48)

The dependent variable is total change in debt over a three-month period following the implementation, that is, $\Delta D_{i,j} = Debt_{i,j}^{April} - Debt_{i,j}^{Feb}$. The control variables include income, marital status, employment status, home ownership, and pretreatment interest rates. Robust standard errors are in parentheses. All values are in British pounds (£).

is imprecisely estimated. For the whole sample the estimate of debt reduction is statistically not different from zero, which implies that the increase in debt in cell 8 is compensated by the total reduction in debt in other cells. Excluding cell 8, we estimate a £15 reduction in debt. This corresponds to a 17% reduction in debt relative to the control over three months for the whole sample (last row in Table 5).

How should we interpret these results? Individuals in cell 7 reduce credit demand, and there is some evidence of active debt reduction efforts. It may be that this group is not liquidity constrained. Table 6 presents the average treatment effects on new transactions and discretionary payments. For cell 7, we see an explicit effort to reduce new transactions (a total of £19 over three months) and increase payments over and above the minimum payment requirement (a total of £26 over three months). Despite this effort we do not find a significant reduction in total debt, and this is due to the high interest charges brought by the large interest rate hike (see the first column in Table 6). We do not see this type of debt reduction effort in other cells.

Turning to cell 8, recall that we estimate no statistically significant reduction in credit demand and a significant debt accumulation over the three month period for this group (see Table 5, Column 1). As shown in Table 6, individuals in cell 8 do not reduce new transactions, do not increase discretionary payment, and pay higher interest charges. What distinguishes individuals in cell 8 is that they are very active users who make regular payments toward their outstanding credit card balances and they roll over a large amount of debt. Average monthly retail purchases for this cell stand at £153 (see Table 3) in November 2007, much higher than for the second highest cell, cell 7 (£88). What makes cell 8 even more interesting is that 75% of the individuals in this cell were given credit limit increases just prior to the experiment (in October 2007). Prior to this increase,

Table 6
Experimental estimates

Average treatment effects (β):

Cells	ATE (total interest charges)	ATE (total new transactions)	ATE (total discretionary payment)
Cell 1	4.71*	−10.9	−5.22
	(2.88)	(10.7)	(15.9)
Cell 4	4.18*	−2.57	0.92
	(2.26)	(13.6)	(15.7)
Cell 7	9.43**	−19.0*	26.1*
	(2.15)	(11.4)	(13.6)
Cell 8	9.16**	7.35	−29.5
	(2.98)	(24.3)	(35.2)
Cell 9	−2.82	−34.2	23.1
	(3.20)	(41.3)	(33.5)
Whole sample	6.38**	−11.6	7.07
	(1.19)	(8.22)	(9.68)
Excluding cell 8	4.79**	−12.9*	12.2*
	(1.08)	(7.05)	(7.40)

The table presents average treatment effects (ATEs) from three regressions. The dependent variables are total interest charges over three months following implementation (Column 1), total new transactions over three months following implementation (Column 2), and total discretionary payments over three months following implementation (Column 3). The control variables include income, marital status, employment status, home ownership, and pretreatment interest rates. Robust standard errors are in parentheses. Values are in British pounds (£).

approximately 40% of the individuals in cell 8 had high utilization rates (over 75%).[16] It is likely that individuals in cell 8 received credit limit increases in response to their high seasonal purchasing activity and good repayment behavior.[17] The peculiarities of this cell discussed above are not in themselves sufficient to fully understand this group. We know that they are active users of their credit cards and they accumulate debt relatively rapidly. Moreover, the lender appears to use these features for segmentation purposes. An increase in interest rates has much more visible consequences for these individuals than it has for others.

Given the behavior exhibited, borrowers in cell 8 were likely to be constrained by their credit limits prior to the increase in these limits. Further supporting this interpretation, at the end of the data period (May 2008), 45% of the individuals in cell 8 hit high utilization rates. The results here highlight that the group we refer to as "subprime" is in fact a very heterogenous group, and our lender seems to be quite successful in identifying credit-worthy borrowers with high spending patterns. We now turn our attention to the lender and assess how it fares from this treatment.

16 Individuals in other cells also received limit increases prior to the experiment, but the percentage of those who received the increase is much lower in other cells. It is 8.5% for cell 1, 18.1% for cell 4, 32.1% for cell 7 and 60% for cell 9.

17 We checked that these increases are independent of the treatment status. More specifically, the p-value of equality of the percentage of people who received credit limit increases across the treatment and the control in cell 8 is 0.69.

Table 7
Experimental estimates

Average treatment effects: Delinquency and total interest charges

Cells	Control's delinquency rate	ATE for delinquency rate	Control's total interest charges	ATE for total interest charges
Cell 1	0.186**	0.009	61.4**	4.71*
	(0.023)	(0.024)	(2.77)	(2.88)
Cell 4	0.028**	0.002	78.5**	4.18*
	(0.007)	(0.007)	(2.18)	(2.26)
Cell 7	0.022**	−0.004	97.3**	9.43**
	(0.005)	(0.004)	(2.07)	(2.15)
Cell 8	0.002	0.003	83.6**	9.16**
	(0.002)	(0.002)	(2.86)	(2.98)
Cell 9	0.007	−0.003	33.2**	−2.82
	(0.005)	(0.005)	(3.10)	(3.20)
Whole sample	0.036**	0.004	80.0**	6.38**
	(0.004)	(0.005)	(1.22)	(1.19)

Columns (1) and (2) report the intercept and the average treatment effect from a regression in which the dependent variable is a dummy variable that equals one if the account is delinquent for four months, that is, from February to May 2008, and is zero otherwise; Columns (3) and (4) report the intercept and the average treatment effect from a regression in which the dependent variable is total interest charges over three months following implementation (in British pounds), $TInt = \sum_{t=1}^{3} Int_t$, for the months of March to May 2008. The control variables include income, marital status, employment status, home ownership, and pretreatment interest rates. Robust standard errors are in parentheses.

4.3 Implications for the lender: Interest charges and delinquency

Higher interest rates will translate into higher revenue for the lender unless it results in a substantial reduction in credit demand or a sufficient increase in delinquencies. This is in fact the point of the experiment for the lender: to find the highest interest rate it can charge without inducing default or lowering credit demand significantly. In the previous section we show that there is a modest overall reduction in credit demand in the sample, mostly coming from the response of the borrowers in cell 7. Because we see some response in credit demand, we use the same experimental framework to estimate the effect of the treatment on interest charges, that is the lender's revenue.

As shown in Table 6, the treatment generates statistically significant additional interest charges for all cells, except for cell 9. The last two columns of Table 7 present these charges relative to the control groups. In cell 7, the average total three-month interest charges for the control group is £97.3 and the experiment generates £9.4 extra interest charges on average for the lender (approximately 10% higher charges). Note that this is despite the fact that treated borrowers in this cell lower their monthly credit demand. For the whole sample, treated individuals pay about £6 extra interest charges over the three-month period because of the interest rate hike. Given that control groups pay on average £80 interest charges, this corresponds with 8% higher charges imposed on the treated borrowers.

Turning to delinquencies, recall that we do not have a long enough sample to assess the actual default behavior. However, we can observe consistently delinquent accounts over the sample period. We also know that the lender is required to stop interest charges after four months of delinquency. We define a delinquency dummy that takes the value of one if the account is delinquent for four consecutive months (February to May) and is zero otherwise. We than regress this dummy on the treatment dummy to see if the treatment *caused* delinquency in the sample. The first column in Table 7 shows the control's delinquency rate, and the second column shows the estimated average treatment effects.

Not surprisingly, cell 1 has the highest delinquency rate (18.9%), and delinquency rates for cells 8 and 9 are not statistically different from zero. We find no evidence that the lender's experiment caused delinquency in our sample (see statistically insignificant treatment effects in Column 2). Overall, it appears that the five percentage point increase in the interest rate generated extra revenues without inducing significant delinquency for the lender.[18] Cells 7 and 8 (borrowers with low risk and high debt) appear to be particularly profitable cells even though cell 7 exhibits significant sensitivity to higher interest rates.

5. Conclusion

We estimate the sensitivity of credit demand to interest rates using subprime credit card users. We do this with a unique data set on monthly credit card transactions from a subprime credit card company that includes a randomized interest rate experiment. We use a calibration of the standard intertemporal model to quantify the theoretically expected responses to the experimental treatment. We then compare these predicted responses to the minimum detectable effects in the experiment. This demonstrates that the experimental design has sufficient statistical power to detect economically plausible responses.

We estimate a statistically significant reduction in monthly credit demand to a five percentage point increase in interest rates for the whole sample. Because the experiment was performed on the existing clients of our lender, we are able to explore heterogeneity in sensitivities. We find that borrowers who are labelled as "low default risk" and carry forward large amounts of debt (close to their credit limit) comprise the only group that lowers its credit demand significantly. However, this effort does not result in an overall reduction in the debt burden for this group. We estimate virtually no sensitivity to a five percentage point increase in the interest rates among borrowers who pose high default risk to the lender. We also find that "low default risk" borrowers who have spare capacity to borrow do not lower their credit demand when faced with a five percentage point increase in interest rates. This insensitivity directly translates into a significant debt accumulation over three months following the interest rate increase.

[18] As a robustness check, we also define our delinquency dummy as "delinquency only in April and May" and "delinquency only in May" to account for the fact that the treatment may take some time to have an effect. We still find no evidence on the treatment causing delinquency over the short horizon.

As in most experiments (randomized or natural), a caveat regarding external validity applies. In particular, our results may be specific to the state of the business cycle. The year 2008 saw a significant contraction in credit supply in many countries, including the U.K. It is plausible that in this macroeconomic environment some households were more credit constrained than in other periods and that we would see greater sensitivity to borrowing rates during economic expansions.

We believe that the evidence we provide in this paper sheds important light on the sensitivity of credit demand to borrowing rates among low-income households in developed economies. Interest rate sensitivity/insensitivity of subprime borrowers is not only of concern to subprime lenders who want to assess elasticities to maximize profits. These elasticities are major inputs for public policies that target financially fragile households in developed economies. As we show in the paper, lenders in these markets exert considerable effort to gauge heterogenous responses to borrowing rates. Public policies and consumer protection actions should also be fully informed by these responses. Our results are obtained using data from a single lender. However, this lender is an important market player and the risk pricing practices presented here are common throughout the industry. The randomized interest rate experiments undertaken by our lender are also not uncommon, though access to the data is.

Appendix

A.1 Expected economic effects

The generic consumer maximizes his expected life time utility

$$E_0\left[\sum_{t=0}^{T} U(C_t)(1+\delta)^{-t}\right]$$

subject to the asset evolution equation

$$A_{t+1}=(A_t+Y_t-C_t)(1+r_{t+1}),$$

where C_t denotes consumption, δ is subjective discount rate, A_t is assets, Y_t is stochastic labor income, and r_{t+1} is interest rate (can also be stochastic). The first-order condition resulting from this maximization is the well-known Euler equation for consumption

$$U'(C_t)=(1+r_{t+1})(1+\delta)^{-1}E_t\left[U'(C_{t+1})\right],$$

which states that the necessary condition for the lifetime utility maximization is that the marginal utility of consumption in the current period must equal the discounted marginal utility of the next period. (See Deaton 1991).

Let us assume that the per-period utility function takes the CRRA form, that is,

$$U(C)=\frac{C^{1-\gamma}}{1-\gamma},$$

where γ is the coefficient of relative risk aversion. In this functional form, $\frac{1}{\gamma}$ is the elasticity of intertemporal substitution, which measures the responsiveness of the consumption to the interest rate changes. Then the Euler equation is

$$C_t^{-\gamma} = \frac{(1+r_{t+1})}{(1+\delta)} E_t \left[C_{t+1}^{-\gamma} \right],$$

where $E_t[C_{t+1}^{-\gamma}]$ is the expected marginal utility of consumption for $t+1$. Note that if we divide both sides of the above equation by $C_t^{-\gamma}$, we obtain the well- known asset pricing equation

$$1 = \frac{(1+r_{t+1})}{(1+\delta)} E_t \left[\frac{C_{t+1}}{C_t} \right]^{-\gamma}.$$

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