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## **Privacy and Money: It Matters**

By Emanuele Borgonovo, Stefano Caselli, Alessandra Cillo,  
Donato Masciandaro and Giovanni Rabitti

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# Privacy and Money: It Matters

Emanuele Borgonovo<sup>^</sup>, Stefano Caselli<sup>^^</sup>, Alessandra Cillo<sup>^^^</sup>, Donato  
Masciandaro<sup>^^^^</sup> and Giovanni Rabitti <sup>^^^^^</sup>

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One sentence summary: Do people see privacy as an attribute of media of payment?

## Abstract

In the economic literature, a medium of payment has two properties: liquidity and store of value. The fast and increasing development of digital currencies raises the question: is privacy a third attribute? We test these assertions through a laboratory experiment. From the theoretical viewpoint, the experiment relies on the simultaneous combination of Keynes's traditional demand for money and Friedman's forward looking intuition on the role of privacy. Results show that privacy positively matters and increases the overall appeal of a medium of payment, even more for risk prone individuals. Given privacy, the sacrifice ratio between liquidity risk and opportunity cost is relatively high. Within the current debate, the experiment suggests that the future competition between alternative currencies will depend on how the three properties will be mixed in a way consistent with the individual's preferences.

Keywords: Money Demand, Cryptocurrencies, Central Bank Digital Currencies,  
Behavioural Economics

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<sup>^</sup> Department of Decision Sciences, Bocconi University.

<sup>^^</sup> Department of Finance, Bocconi University.

<sup>^^^</sup> Department of Decision Sciences and Igier, Bocconi University.

<sup>^^^^</sup> Department of Economics and Baffi Carefin Center, Bocconi University, and SUERF.

<sup>^^^^^</sup> Department of Decision Sciences, Bocconi University.

## INTRODUCTION

The protection of privacy is surely an important issue in the information age (1). Then, can privacy play a role in explaining the shape of money demand? More precisely, is privacy the third attribute that can explain the demand of both traditional and new media of exchange either already existing, as the cryptocurrencies, or in the pipeline, such as the widely debated central bank digital currencies?

The general interest of these questions is evident if we observe three stylized facts. First, the resilience of public paper currencies, where most of these currencies are in the form of large-denomination banknotes, appreciated for their anonymity. Second, the use of cryptocurrencies (2-5), in which cryptographic procedures are used to protect privacy, where a relevant share of cryptocurrency users seem to like the anonymity property (6). Third, in the emerging debate about the issuing of central bank digital currencies (7-13) the counterparty anonymity is a relevant issue.

Therefore, a natural question arises: does money demand depend on privacy? So far, the economic literature has investigated the possible association between money and privacy of transactions (14-17). Any kind of money can be considered a “store of memory” (18,16,15). The potential relevance of privacy costs in motivating money demand is highlighted by the famous Milton Friedman’s statement (19): “I think the Internet is going to be one of the major forces for reducing the role of government. The one thing that’s missing but that will soon be developed is a reliable e-cash, a method whereby on the Internet you can transfer funds from A to B without A knowing B or B knowing A.”<sup>1</sup> . Twenty years later, it is a matter of fact that with the ongoing development of virtual exchanges the costs of opacity – i.e. anonymity – can sensibly increase. But is such association so relevant and general that we can consider privacy as a third property of the demand for money?

Our answer is positive and is based on a novel specification of the demand for money where a medium of payment (MOP) has simultaneously three properties: the first two are the MOP’s standard functions as a medium of exchange and as a store of value – i.e. the Keynesian transaction and speculative motives<sup>2</sup> (21,22)- while the third one is the novel function as a store

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<sup>1</sup> NTUF (1999), <https://www.youtube.com/watch?v=6MnQJFEVV7s>.

<sup>2</sup> “Let the amount of cash held to satisfy the transactions (...) be M1, and the amount held to satisfy the speculative motive be M2. Corresponding to these two compartments of cash, we then have two liquidity functions L1 and L2 (J.M. Keynes, 1936, p.168)” (20).

of privacy. The robustness of the new specification has been tested through a laboratory experiment.

## RESULTS

### Methodology

Let  $\mathbf{x}^a = (x_1, x_2, x_3)^a$  indicate a payment method of an amount of  $a$  EUR, with three attributes  $x_1, x_2, x_3$ , where  $x_1$  is Illiquidity Risk (IR),  $x_2$  Expected Return (ER), and  $x_3$  Anonymity (ANM). The methodology consists of three parts.

First, we want to determine, when two MOPs differ only in the anonymity dimension, how relevant is – if any - the preference for anonymity. We use two approaches, in Part I and in Part II of the experiment. Under the first approach, in Part I, we select 17 media of payment (points) of  $a$  EUR, with different levels of IR, ER, and ANM. For each of these MOPs, we are interested in assessing the value that subjects assign. We elicit the indifference value  $z_i$  such that  $\mathbf{x}_i^a \sim z_i$  for  $i=1, \dots, 17$  (the 18<sup>th</sup> MOP is the standard cash amount of 100 EUR). Hence, we end up with 9 comparisons between two MOPs which have the same level of IR and ER, while differing in the ANM dimension. Any value difference between these pairs is attributed only to the anonymity dimension (see Table S1 in the Supplementary Material for a description of the structure of Part I). The second approach consists of dealing with a portfolio allocation. Indeed, in Part II, we consider a portfolio with two MOPs,  $(0,0, No)^a$  and  $(0,0, Yes)^b$  and elicit the optimal money allocation  $(a^*, b^*)$  between the two MOPs, with  $a^* + b^* = 100$ . The bigger  $b^*$ , the higher is the subjects' preference for anonymity.

Second, we want to understand the relative importance of anonymity, with respect to IR and ER. In Part I, the 18 MOPs corresponded to a vertex of the hypercube of a full factorial design with two factors, illiquidity risk and return, at 3 levels (Low, Medium, High), and a third factor, anonymity, at two levels (Yes, No). Note that the origin represents the MOP with no illiquidity risk, no return and anonymous and is, therefore, equivalent to standard cash. For each of these points, which differ in the IR, ER, and ANM, subjects assign a value. Hence, we can determine which factor has a higher impact on the evaluation through standard statistical methods.

In the final part of the experiment, we aim to understand in a context of anonymity - cryptocurrencies or central bank digital currencies, assuming credible anonymity for both types of MOP - how subjects trade-off between risk and return. Here we consider three types of MOPs:

the first two are the same as in the Part II. The third MOP is an anonymous and risky MOP  $(x_1, x_2, Yes)$  with three different levels of IR and three different levels ER. Hence, we create 9 portfolios with these three types of MOP, and elicit the optimal money allocation  $(a^*, d^*, c^*)$  with  $a^* + c^* + d^* = 100$  among the three MOP,  $(0,0, No)^{a^*}$ ,  $(0,0, Yes)^d$ ,  $(x_1, x_2, Yes)^{c^*}$ . The third MOP is the only one that has a risk-return component different from zero. Hence, the higher the value of  $c^*$ , the more the subject is willing to allocate money to the anonymous, profitable and, hence, risky MOP (see Table S2 in the Supplementary Material for a description of the structure of Part II (question 18) and Part III).

### **Subjects and Procedure**

The subjects were 98 students from Bocconi University, with different background. Subjects were paid a flat fee of 10 EUR. At the end of the experiment, 10% of subjects could play for real one of the choices. We used the Prince method because it improves several aspects of existing incentive systems (23). The incentive compatibility is very clear. Indeed, the choice question implemented for real was selected before the experiment started, and subjects' answers were framed as instructions to the experimenter. Before starting the experiment, subjects randomly picked a sealed envelope. At the end of the experiment, 10% of the envelopes were selected and the subjects owning one of those envelopes could play for real the choice question (see Supplementary Material for a detailed description).

The experiment was computer run with a minimum of three experimenters per session, with an average of 12 subjects per session. The experiment lasted, on average, one hour: instructions were read aloud (see Supplementary Material for the instructions provided to the subjects), for twenty minutes, then subjects took a seat and could always read the instructions. The procedure to elicit the indifference values was made clear to the subjects, for each of the three Parts.

In all the three Parts, the elicitation were performed via a choice task and the order of the elicitation within each part was random. The choice task is known to be preferred to the matching one (24,25). The innovative aspect in our implementation has consisted in the fact that each step of the bisection procedure was visible to subjects, while usually it is not (see the Supplementary Material for a detailed description). The main reason for this was to make the experiment of a standard length. Fig. 1 provides an example of the screenshot in Part I.

**INSTRUCTIONS FOR ENVELOPE OF TYPE THETA**  
 In each of 4 envelopes of type theta, option A is a card (currency) of 100 Euro with three different features: Liquidity Risk, Expected Return, Anonymity; the option B is a money amount of x Euro. The money amount x varies in different envelopes. The note in each envelope of type theta is as follows.

	Liquidity Risk	Expected Return	Anonymity
Option A:	1.00%	20.00%	No

Option B: x Euro

Your envelope may contain two Options of the following form.  
 For small values of x you prefer Option A. For large values of x you prefer Option B. There is a threshold value above which you prefer Option B, and below which you prefer Option A.

For each number x, instruct which Option you want to be taken from the envelope if its content is as above, by clicking on Option A or Option B, in the next type theta questions. You will get what you want.

Please, select the option you prefer, by clicking on the option. Once you have selected the option, you will be asked if you want to confirm your choice.

Option A				Option B			
	Liquidity Risk	Expected Return	Anonymity		Cash Amount		
<input checked="" type="checkbox"/>	Option A	1.00%	20.00%	No	Option B	100	<input checked="" type="checkbox"/>
	Option A	1.00%	20.00%	No	Option B	80	
	Option A	1.00%	20.00%	No	Option B	90	

**Fig. 1. The screenshot of Part I.** Option A was a MOP with three different values for each attribute, while Option B was a cash amount. The bisection procedure was clearly visible to the subjects.

To test for response errors, we repeated a total of eleven choice questions. Precisely, at the end of Part I, for each subject we repeated the third iteration (close to the indifference value) for 7 randomly selected elicitations. These elicitations can be different for each subject. At the end of Part III, for each subject, we repeated the second iteration or the first one if the second one was not present for 4 randomly selected elicitations.

### Internal validity

For 18 of the 98 subjects, the experiment ended prematurely. Indeed, to prevent collecting data of subjects not understanding the task or not being serious about it, the experiment ended prematurely for subjects who repeatedly preferred dominated options. This left us with 80 subjects.

The registered consistency rates, namely, the rates of identical answers between the repeated and the original choice, are 85.7% for Part I, and 75% for Part III. These figures are, respectively, higher than average and consistent with rates with the ones found in the literature (26). We did not register violations of monotonicity at an aggregate level. Indeed, in Part I, for a fixed level of IR, the mean values of  $z_i$ , assessed values of MOP, increased in the ER, and vice versa (for a fixed level of ER, they were decreasing in IR). These results hold in case of anonymity and in case of no anonymity as well.

The Prince method is well known to make incentive compatibility very clear. Indeed, in our experiments the subjects knew that they were going to get an amount that depended on what

they stated and on the number in the sealed envelope. Hence, they understood it was in their own interest to state their true preferences. We believe that the innovative methodological aspect of combining the Prince method and the bisection procedure, which differently from usual was now visible to subjects, might have been a reason for these robust results.

### **Does anonymity matter? How much?**

This issue was specifically investigated in Parts I and II of the experiment. As Table 1 shows, when facing two MOPs differing only on the anonymity dimension, subjects assigned to the anonymous MOP a value on average 1.44% higher than to the non-anonymous MOP. Thus, anonymity *per se* matters. Moreover, for risk prone subjects, the increase was 30% greater than for risk averse subjects. In other words, risk prone subjects seem to give more value to the property of money as store of privacy. Note that the more an individual's risk propensity is associated with crime propensity (34), the more individuals involved in illegal activities are likely to value anonymity.

In Part II, elicitation 18, the subjects were asked to communicate their preferences for allocating the available budget between an anonymous MOP with zero illiquidity risk and zero return and a non-anonymous medium of exchange with zero illiquidity risk and zero return. Thus, the two MOPs differed only in the third attribute (anonymity). The majority of subjects, 60 over 80, allocated the entire budget to the anonymous medium of exchange. In Table S2, question 18, the average allocation in the anonymous MOP was 82 EUR. Again, anonymity *per se* does matter and subjects consider it as a valuable third attribute.

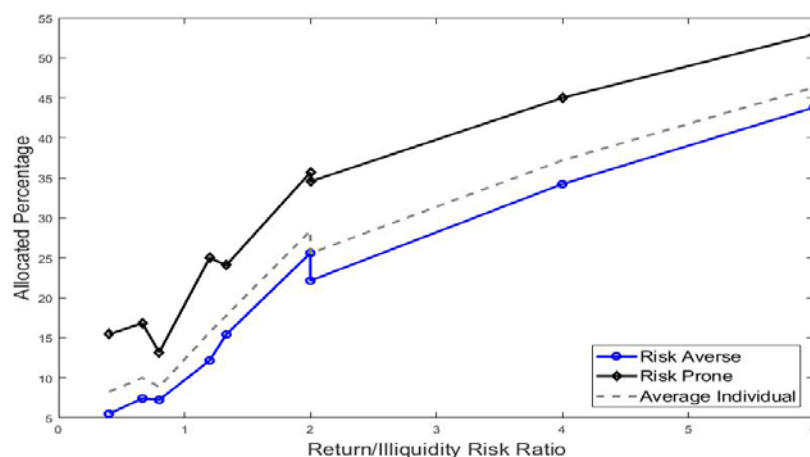
We designed our experiment also to allow one to understand how much anonymity matters when compared to illiquidity risk and expected return. To obtain this insight we analyse the aggregated answers to the first 17 questions using methods of design of experiments (see Supplementary Material for a detailed statistical analysis). We treated the data recommended in design of experiments for non-normal responses (see (27-29)). In particular, we fitted the data with a Poisson regression model (see Supplementary Material for full details). The results evidence that risk and return are strongly statistically significant when taken individually, with anonymity being less relevant but still significant. Illiquidity risk and expected return are also involved in a statistically significant interactions, while anonymity is not involved in interactions with the remaining attributes. The coefficients of the generalized linear model (GLM) represent the

expected change in value of the MOP following a percentage increase in the covariate, on a logarithmic scale.

The values of the coefficients of the generalized linear model (Table S3) suggest that the expected return has a greater influence than illiquidity risk, which in turn is more important than anonymity. To confirm this ranking, we estimated additional measures of statistical association known as global importance measures (see (30) among others). We considered four dependence measures, denoted here by  $\eta_i, \delta_i, \beta_i^{KS}, \beta_i^{Ku}$ , that rank covariates based on contribution to variance, on the separation between the marginal and unconditional density and cumulative distribution function of Y (see the Supplementary Material for the technicalities on the global importance measures). The higher the values of these quantities, the stronger the statistical dependence of the dependent variable on the covariates, IR, ER, and ANM in our case. As Fig. S2 shows (see Supplementary Material), all these dependence measures agree in ranking expected return, as the most important attribute, followed by illiquidity risk, and anonymity.

### If cryptocurrencies, how do people trade-off risk with return?

Given the relevance of the expected return property, we investigated whether there is a threshold level of return for which the subjects are willing to allocate a significant portion of their portfolio to a risky and anonymous MOP. The risk return ratio curves measured experimentally are given in Fig. 2.



**Fig. 2. Return/Risk curves.** On the horizontal axis we find the ratio between the return (in percentage) and the illiquidity risk. The black (—♦—), blue (—o—) and gray (— —) lines represent the allocations of a risk prone, risk averse and average individuals, respectively.



The graph displays three curves. Each curve represents the percentage of the current budget that each subject would allocate to a third MOP (the other two MOPs have non risk, no return and differ in the anonymity dimension), which is anonymous and characterized by an increasing “return/illiquidity risk” ratios, for risk prone (black, –♦), risk averse (blue, – o –), and average (gray, - -) individuals, respectively. For all types of subjects, the allocated percentage increases with the increase of the ratio between the return and the illiquidity risk. That is, the riskier the asset, the lower the percentage allocated to it, if such risk is not compensated by a corresponding increase in return. It is worth noting that risk prone investors systematically allocate more to the anonymous and risky MOP than risk averse individuals.

Thus, the analysis of the experimental results in Fig. 2 suggests that risk attitudes influence the amount allocated but not the trend. The trend is common to all individuals and registers an increasing allocated percentage as the ratio return/illiquidity risk increases.

However, note the diminishing marginal sensitivity (initial steep ascent and then more moderate growth) and the fact that one achieves a substantial (greater than 20%) allocation only for “return/illiquidity risk” ratios greater than 2. Consider now allocating more than half of the budget to the risky MOP. The experimental results in Fig. 3 suggest that the return must be at least 5 times greater than the illiquidity risk to have a risk adverse investor allocating more than half of his current budget. In other words, the sacrifice ratio between the two properties of liquidity and return is relatively high: to accept higher illiquidity risks the individuals call for a more than proportional increase in the expected return.

These results could be interpreted as signalling that anonymous MOPs are considered attractive if they promise gains substantially greater than the associated risk. This can explain the initial run to bitcoins, whose returns have been very high in the initial phase, overwhelming the associated illiquidity risk. They can also explain the appetite for the new emerging crypto currencies that can produce high returns in spite of an associated non-negligible illiquidity risk.

At the same time, consider a cryptocurrency emitted by an entity whose illiquidity risk is small, such as a Central Bank. In this case, the denominator in the “return/illiquidity risk” ratio is small. Then, as soon as the return is not negligible the ratio is high. For illustration purposes, consider a thought experiment on a European Central Bank cryptocurrency. For such an MOP, the default probability is close to zero or even zero. If it were zero, then any return would make the “return/illiquidity risk” infinite. However, let us set the illiquidity risk at  $10^{-5}$  per year.

Then, a yearly return of 0.0001 would lead to a return/illiquidity risk of 10, again in a region in which investors would allocate a considerable amount of their capital to this MOP.

## **DISCUSSION**

The results of our experiments show that: 1) anonymity matters; 2) the opportunity cost is the more relevant property of money; 3) combining the three properties of money is likely to increase the interest in a medium of exchange; 4) risk prone individuals like anonymity even more, which might explain the relationship between anonymity and illegal activities; 5) given the level of anonymity, the sacrifice ratio between illiquidity risk and return is relatively high: to accept higher illiquidity risks the individuals call for a more than proportional increase in the expected returns.

Given that the experiments confirm that anonymity matters, two considerations follow. On the one hand, cash can maintain its appeal as an anonymous MOP. On the other hand, the more other MOPs can be trusted in offering anonymity, while balancing illiquidity risk and expected return, the more likely the crowding out of cash will be.

Finally, policy implications emerge for MOP suppliers such as banks, central bankers and private firms. Banking currencies could be challenged as MOPs by a lack of anonymity and by the presence of low expected returns, features that make cryptocurrencies more attractive. Similarly, the success of a cryptocurrency will depend on its ability to decrease the illiquidity risk, to increase the expected return, while credibly guarantee anonymity. For a central bank digital currency, its unique feature is that it is an electronic MOP and a public currency, as well. The experiment shows that its attractiveness depends on how it is designed, in terms of the level of privacy and interest-bearing mechanisms. In principle the illiquidity risk of a central bank digital currency is very low, but at the same time it seems unlikely that individuals will consider it as anonymous as cash. Our results show that offering a yield could be a trigger to increase its appeal.

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## TABLES

IR	ER	Anonymity Shift	Average Change in Value
0%	0%	No ->Yes	+2.94
1%	0%	No ->Yes	+0.94
10%	0%	No ->Yes	+0.5
0%	5%	No ->Yes	+1.06
1%	5%	No ->Yes	+2.00
10%	5%	No ->Yes	-0.38
0%	20%	No ->Yes	+2.25
1%	20%	No ->Yes	+2.00
10%	20%	No ->Yes	+1.625

**Table 1. Average change in value due to preference for anonymity.** 9 pairs of MOP. Each pair the two MOP differ only in the ANM dimension. Last column: the average increase in value due to the presence of an anonymous MOP.

### List of Supplementary Materials

Materials and Methods.

**Fig. S1.** Full factorial design points used in this work.

**Fig. S2.** Measures of statistical dependence.

**Table S1.** Elicited mean indifference values for the 17 MOP.

**Table S2.** The 10 portfolios in Part II and Part III and their budget allocation.

**Table S3.** Statistical analysis results for the generalized linear regression.

## Supplementary Materials for

# Privacy and Money: It Matters

Emanuele Borgonovo<sup>^</sup>, Stefano Caselli<sup>^^</sup>, Alessandra Cillo<sup>^^^</sup>, Donato  
Masciandaro<sup>^^^^</sup> and Giovanni Rabitti <sup>^^^^^</sup>

January, 2019

Correspondence to: [alessandra.cillo@unibocconi.it](mailto:alessandra.cillo@unibocconi.it)

The pdf file includes:

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Reference: please refer to the main paper, as suggested by the journal.

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<sup>^</sup> Department of Decision Sciences, Bocconi University.

<sup>^^</sup> Department of Finance, Bocconi University.

<sup>^^^</sup> Department of Decision Sciences and Igier, Bocconi University.

<sup>^^^^</sup> Department of Economics and Baffi Carefin Center, Bocconi University, and SUERF.

<sup>^^^^^</sup> Department of Decision Sciences, Bocconi University.

## MATERIALS AND METHODS

### METHODS

#### Elicitation procedure

The experiment consisted of three Parts. In Part I, we used a standard bisection procedure to determine the 17 indifference values. As Table S1 shows,  $x_i^{100}$  is a MOP of 100 EUR with  $i=1, \dots, 17$ . The 17 MOP of 100 EUR have been constructed by combining three levels of IR (0%, 1%, 10%), three levels of ER (0%, 5%, 20%), and two levels of ANM (Yes/No).

In Part II, we elicited, via an iteration procedure, the optimal money allocation  $(a^*, b^*)$  between the two MOP,  $(0,0, No)^a$  and  $(0,0, Yes)^b$ . Subjects had to choose between two portfolios, Options A and B, which differed in the allocation of the 100 EUR between the two MOP:

$$\text{Option A: } ((0,0, No)^{a-10} ; (0,0, Yes)^{b+10}))$$

$$\text{Option B: } ((0,0, No)^a ; (0,0, Yes)^b))$$

where  $a + b = 100$  EUR. We started with  $a=10$  EUR. If subjects chose Option B, we kept adding 10 EUR until they switched to Option B. The experiment ended and then we stored the midpoint values,  $(a^*, b^*)$ .

In Part III, we elicited via an iteration procedure, the optimal money allocation  $(a^*, d^*, c^*)$  between the three MOP  $(0,0, No)^{a^*}$ ,  $(0,0, Yes)^d$ ,  $(x_1, x_2, Yes)^{c^*}$  where  $(x_1, x_2, Yes)^{c^*}$  have been constructed by combining three levels of IR (5%, 15%, 25%), and three levels of ER (10%, 20%, 30%), always in an anonymous context (ANM=Yes). Subjects had to choose between two portfolios, Options A and B, which differed in the allocation of 100 EUR between the three MOP. For example:

$$\text{Option A: } ((0,0, No)^{a^*} ; (0,0, Yes)^{d+10} ; (5\%, 10\%, Yes)^{c^*-10}))$$

$$\text{Option B: } ((0,0, No)^{a^*} ; (0,0, Yes)^d ; (5\%, 10\%, Yes)^{c^*}))$$

where  $a^* + d + c^* = 100\text{EUR}$ , and  $a^*$ , elicited in Part II, was allocated in the first payment under both Option A and B. If subjects chose Option B, we kept increasing  $c$  by 10 EUR until they chose Option B, in which case we stopped, took the midpoint, and stored it.  $c^*$  can be interpreted as the fraction invested in the risky payment. Table S2 provides the elicitation in Part II and Part III.

## **Bisection procedure**

### **Part I**

We wanted to find the amount  $z$  that makes the subject indifferent between option A and option B. We started with  $z = 100$ . There were two possible scenarios:

(i) If A was chosen we increased  $z$  by 20 until B was chosen. We then halved the step size and decreased  $z$  by €10. If A [B] was subsequently chosen we once again halved the step size and increased [decreased]  $z$  by €5, etc..

(ii) If B was chosen we decreased  $x$  by 20 until A was chosen. We then halved the step size and increased  $z$  by €10. If B [A] was subsequently chosen we once again halved the step size and decreased [increased]  $z$  by €5, etc..

The elicitation ended when the difference between the lowest value of  $x$  for which B was chosen and the highest value of  $x$  for which A was chosen was less than or equal to €5. The midpoint was taken and stored.

In case a subject clicked 6 consecutive times on A (or B), the experiment ended prematurely for that subject. This check was inserted to avoid severe and consecutive violations of stochastic dominance.

### **Part II**

There were two possible scenarios:

i) If B was chosen we increased  $x$  by 10 units until A was chosen. Then the experiment stopped and the midpoint between the highest value of  $x$  for which B was chosen and the highest value of  $x$  for which B was not chosen was stored.



ii) If A was chosen then the experiment stopped and the midpoint between 0 and 10 was stored.

### **Part III**

The selected option became option A in the next question. Option B in the next question was then the option B in the previous with  $c$  which is either increased or decreased by 10.

There were three possible scenarios:

i) If B was chosen we increased  $c$  by 10 until A was chosen. Then the experiment stopped and the midpoint between the highest value of  $y$  for which B was chosen and the highest value of  $y$  for which B was not chosen was stored.

ii) If A was chosen then stop and store midpoint between 0 and 10.

iii) If B was chosen without any change, then the experiment stopped and the highest value for which B was chosen was taken.

If  $a^* = 100$  in elicitation 18, then in part III the second payment had by default an allocation of 0.

### **Statistical analysis**

The experimental setting for the first 17 questions is a full factorial design, with two factors, illiquidity risk and expected return, at 3 levels (Low, Medium, High), and a third factor, anonymity, at two levels (Yes, No). The design has a total of  $3^2 \times 2 = 18$  points (point 18<sup>th</sup> is the standard cash anonymous MOP with no risk and no return). A full factorial design is an experimentation plan that allows one to investigate the main and interaction effects of the three factors which can vary simultaneously. It contains all the 18 combinations of the three factors and it is represented by the hypercube in Fig. S1. Each of the 80 participants provided an answer for each point, for a total of 1440 responses.

As suggested in the main text, we fitted the data via a generalized regression model of the form:

$$E[Y] = \exp(\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_{1,2} X_1 X_2 + \alpha_{2,3} X_2 X_3 + \alpha_{1,3} X_1 X_3 + \alpha_{1,2,3} X_1 X_2 X_3)$$

where  $X_1 = IR$ ,  $X_2 = ER$ ,  $X_3 = ANM$ . This model belongs to the well-known class of generalized linear model.

Table S3 reports the values of the statistical analysis. The model fit is strongly significant (p-value  $< 2.2e-16$ ). Then, we can study and interpret the significance of the coefficients of the main effects  $\alpha_1, \alpha_2, \alpha_3$  and the interaction effects  $\alpha_{1,2}, \alpha_{2,3}, \alpha_{1,3}, \alpha_{1,2,3}$ . The values in Table S3 show that the coefficients of  $X_1$  and  $X_2$  and of the interaction term  $X_1X_2$  are strongly statistically significant. The coefficient of  $X_3$  is weakly significant, and the remaining coefficients are deemed of very low statistical significance. This result would indicate that the additive part of the model prevails over the part associated with interactions. It also indicates that the first two covariates, namely illiquidity risk and expected return, tend to be more influential than the third covariate, namely, anonymity.

To corroborate this insight, we computed alternative measures of statistical dependence between the output response (the value assigned by the subjects) and the three attributes. The rationale is that if all the available indices lead to the same indication concerning the attribute importance, then our inference concerning the relevance of the attribute is robust. To do so, we use importance indicators introduced in the literature under the name of global importance measures, which are recognized to be among the most robust ways to infer parametric importance and to measure statistical dependence between a variable of interest and other variables on which the variable of interest depends in a statistical fashion.

The global sensitivity measures we compute are first order variance-based sensitivity measures, a sensitivity measure based on the distance between densities and two sensitivity measures based on the distance between cumulative distribution functions. Formally, let  $(\mathbf{X}, \mathbf{B}(\mathbf{X}), P_{\mathbf{X}})$  denote the probability space associated with the vector of random variables  $\mathbf{X} = \{X_1, X_2, \dots, X_n\}$ , with  $\mathbf{X} \in \mathbf{X}$ ,  $\mathbf{X} \subseteq R^n$ . Then, one considers that the random variable of interest,  $Y$ , depends on  $\mathbf{X}$  as  $Y = g(\mathbf{X}) + \dot{\alpha}(\mathbf{X})$ , where  $g: \mathbf{X} \mapsto R$  and  $\dot{\alpha}(\mathbf{X})$  is a stochastic error term with zero mean. Then, a first measure of statistical dependence between  $Y$  and any of the random variables  $X_i$  is given by the contribution of  $X_i$  to the variance of  $Y$  measures as

$$\eta_i = \frac{V\{E[Y | X_i]\}}{V[Y]}.$$

The quantity  $\eta_i$  is the variance-based importance of variable  $X_i$  (31) and coincides with Pearson's correlation ratio. This global importance measure is widely used in the literature; however, it does not satisfy Renyi's postulate D concerning measures of statistical dependence (32). We then accompany this sensitivity measure by the calculation of additional sensitivity measures that satisfy such postulate. In particular, we consider the sensitivity measure:

$$\delta_i = \frac{1}{2} \mathbf{E}_{X_i} \left[ \int_Y |f_{Y|X_i}(y | X_i) - f_Y(y)| dy \right],$$

where  $f_Y(y)$  and  $f_{Y|X_i}(y | X_i)$  are, respectively, the marginal density of  $Y$  and the conditional density of  $Y$  given  $X_i$ , and the expectation is taken with respect to the marginal distribution of  $X_i$ . Thus,  $\delta_i$  measures statistical dependence as the distance between densities and it can be shown that its value is null if and only if  $Y$  is independent of  $X_i$ . We also estimate two global sensitivity measures that consider the distance between cumulative distribution functions:

$$\beta_i^{KS} = \mathbf{E}_{X_i} \left[ \sup_y |F_{Y|X_i}(y | X_i) - F_Y(y)| \right],$$

and

$$\beta_i^{Ku} = \mathbf{E}_{X_i} \left[ \sup_y \{F_{Y|X_i}(y | X_i) - F_Y(y)\} + \sup_y \{F_Y(y) - F_{Y|X_i}(y | X_i)\} \right],$$

where  $F_Y(y)$  and  $F_{Y|X_i}(y | X_i)$  are the marginal cumulative distribution function of  $Y$  and the conditional cumulative distribution function of  $Y$  given  $X_i$ , respectively. The quantities  $\beta_i^{KS}$  and  $\beta_i^{Ku}$  measure the distance between  $F_Y(y)$  and  $F_{Y|X_i}(y | X_i)$  through the Kolmogorov-Smirnov and the Kuiper metrics, respectively. A thorough account on the theoretical aspects of these sensitivity measures can be found in (30) (details on their estimation can be found in (33)). To our purposes, it suffices to say that the highest the values of these quantities ( $\eta_i, \delta_i, \beta_i^{KS}, \beta_i^{Ku}$ ), the stronger the statistical dependence of  $Y$  on  $X_i$ .

## MATERIALS

### Constructions of the envelopes

98 subjects participating at the experiment. An average payment of roughly 20 EUR per subject is reasonable to be expected. Since each of them had 10 EUR as flat fee, and 10 of them played for real one of the choice questions, we constructed 100 envelopes with an

average amount of 100 EUR. Each choice question was present at least once among the 100 envelopes.

For each subject and for each question, we stored the indifference value (IV).

In Part I, the choice questions were represented by the Option A as described in the text. Option B was a random number (RN) in the interval  $[EV(A)-0.1*EV(A), EV(A)+0.1*EV(A)]$ . If  $RN \geq IV$ , then the subject –had he faced exactly that question with that RN- would have preferred the RN. That is what he got. If  $RN < IV$ , then the subject would have preferred the Option A. That is what he got. Getting the Option A, means playing Option A, with its risk component. In case subjects won an anonymous payment method, we provided them with cash, otherwise with a bank transfer.

In Part II, for an EV maximizer the optimal cash  $a^*$  to allocate would be 100 (assuming positive assessment of anonymity). Hence, we constructed the Options in Part II as follows:

Option A:  $((0,0, No)^0 ; (0,0, Yes)^{100})$

Option B:  $:( (0,0, No)^{10} ; (0,0, Yes)^{90} )$

where  $a^*=10$  was our selected number in the envelope (RN). If  $RN \geq IV$ , then the subject would have preferred the Option A. That is what he got. If  $RN < IV$ , then the subject would have preferred Option B. That is what he got.

In Part III, for most of the choice questions an EV maximizer would have allocated most of the money under the payment method III (for the choice questions 19, 20, 21, 23, 24), and under the payment method II (for the choice questions for 22, 25, 26, 27). The selected number  $c^*$  in the envelope was a RN in the interval  $[60-0.1*60; 60+.1*60]$  (or  $[10-0.1*10; 10+.1*10]$ ), allocated under payment method III. Hence, we let the elicited subject specific  $a^*$  under payment method I (which then was revealed to the subject at the end of the experiment), while the complement to 100 allocated under payment method II. Below, an example on how the options in Part III were structured:

Option A:  $((0,0, No)^{a^*}; (0,0, Yes)^{100-a^*-RN+10}; (5\%, 10\%, Yes)^{RN-10})$

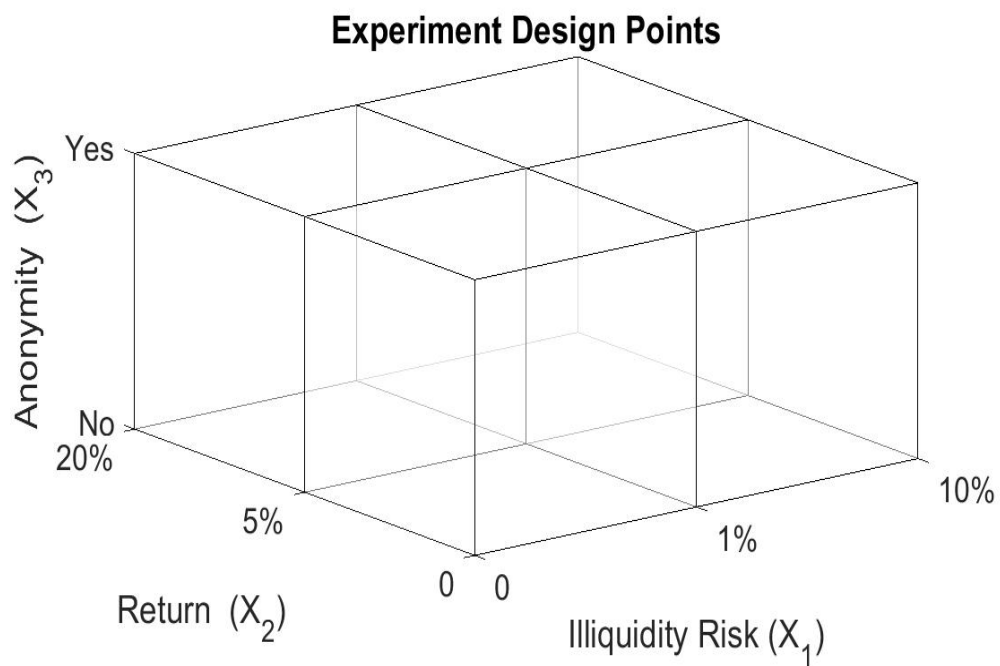
Option B:  $((0,0, No)^{a^*}; (0,0, Yes)^{100-a^*-RN}; (5\%, 10\%, Yes)^{RN})$

where  $a^*$  was elicited in Part II. If  $RN \geq IV$ , then the subject would have preferred the Option A. That is what he got. If  $RN < IV$ , then the subject would have preferred Option B. That is what he got.

**Instructions for the subjects**

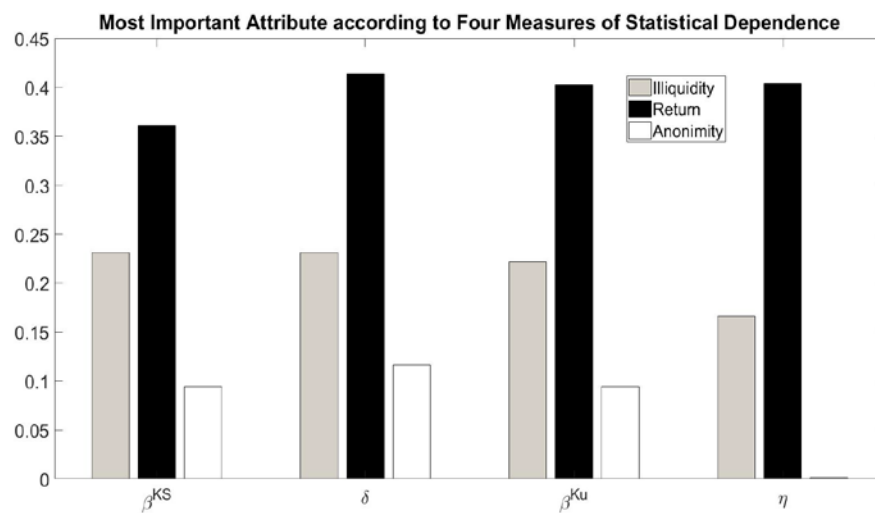
Available upon request to [alessandra.cillo@unibocconi.it](mailto:alessandra.cillo@unibocconi.it)

**Fig. S1.**



**Fig. S1. Full factorial design points used in this work.** Illiquidity risk and return have three levels, while anonymity has two levels.

**Fig. S2.**



**Fig. S2. Measures of statistical dependence.** Measures of statistical importance of IR, ER, and ANM.

**Table S1.**

	<b>IR</b>	<b>ER</b>	<b>ANM</b>	<b>Mean (SD)</b>	<b>EV</b>
1	0%	0%	No	97 (11)	99
2	1%	0%	No	93 (10)	98
3	10%	0%	No	80 (15)	89
4	0%	5%	No	106 (5)	104
5	1%	5%	No	103 (9)	103
6	10%	5%	No	90 (13)	94
7	0%	20%	No	124 (10)	119
8	1%	20%	No	121 (12)	118
9	10%	20%	No	108 (17)	108
10	1%	0%	Yes	94 (12)	99
11	10%	0%	Yes	81 (14)	90
12	0%	5%	Yes	107 (8)	105
13	1%	5%	Yes	105 (13)	104
14	10%	5%	Yes	90 (14)	95
15	0%	20%	Yes	127 (14)	120
16	1%	20%	Yes	123 (12)	119
17	10%	20%	Yes	109 (16)	108

**Table S1. Elicited mean indifference values for the 17 MOP.** In the second last column the mean indifference values (standard deviation) and in the last column the predicted value for an expected value maximizer.



**Table S2.**

Questions	Portfolio	Mean Elicited Values
18	$((0^a, 0^a, No^a); (0^b, 0^b, Yes^b))$	$(a^*=18, b^*=82)$
19	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (5\%^c, 10\%^c, Yes^c))$	$c^*=28$
20	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (5\%^c, 20\%^c, Yes^c))$	$c^*=37$
21	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (5\%^c, 30\%^c, Yes^c))$	$c^*=46$
22	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (15\%^c, 10\%^c, Yes^c))$	$c^*=10$
23	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (15\%^c, 20\%^c, Yes^c))$	$c^*=18$
24	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (15\%^c, 30\%^c, Yes^c))$	$c^*=26$
25	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (25\%^c, 10\%^c, Yes^c))$	$c^*=8$
26	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (25\%^c, 20\%^c, Yes^c))$	$c^*=9$
27	$((0^{a^*}, 0^{a^*}, No^{a^*}); (0^d, 0^d, Yes^d); (25\%^c, 30\%^c, Yes^c))$	$c^*=16$

**Table S2. The 10 portfolios in Part II and Part III and their budget allocation.** For each portfolio, we elicit the optimal money allocation,  $(a^*, b^*)$  for question 18, and  $c^*$  for the other ones. The last column reports the mean elicited values.

**Table S3**

<b>Coefficients</b>	<b>Estimate</b>	<b>P-value</b>	<b>Significance</b>
<b>(Intercept)</b>	4.578822	<2e-16	****
IR	-0.093505	<2e-16	****
ER	0.124882	<2e-16	****
ANM	0.024475	0.0641	*
IRxER	0.011400	0.0402	**
IRxANM	-0.011907	0.2638	
ERxANM	-0.004402	0.6520	
IRxERxANM	0.005302	0.4984	

**Table S3. GLM coefficients and their significance.** Significance codes: '\*\*\*\*' = very strong '\*\*\*' = strong; '\*\*' = relevant; \* = weak.