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Essays on FinTech

Thesis

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I hereby declare that

1. I have written this dissertation independently and without the aid of unfair or unauthorized resources. Whenever content was taken directly or indirectly from other sources, this has been indicated and the source referenced.

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Date 31. 05. 2020

Signature

Essays on FinTech

Christoph Scheuch

May 31, 2020

To my grandfather

Acknowledgments

First and foremost, I want to thank my advisor Alex Mürmann for his guidance and support since the very first day I joined the Vienna Graduate School of Finance.

I also want to thank all the wonderful people I met at graduate school for the stimulating discussions and sense of humor that carried us through years of tedious coursework and countless hours of exasperating research. Most notably, I want to thank Stefan Voigt for not only being a brilliant coauthor but also the best colleague ever. I cannot imagine the last years without our collaboration and the continuous feedback we have thrown at each other.

Moreover, I would like to express my gratitude to all my dear friends and partners, who, over all these years, countered my frequent complaints with encouragement and vital distraction from work. I feel very blessed to be part of such a wonderful environment. This thesis rests on the support of these people.

Last but not least, I want to thank my family for providing me with the freedom to pursue my dreams. I wish that my grandfather could see that I fulfilled the one he had envisioned for me.

Summary

FinTech typically describes the application of novel technologies in the financial services sector. These technological innovations aim to compete with traditional financial technologies and improve user experience on a broad range of financial applications. Examples range from peer-to-peer investing services and new settlement procedures to the use of smartphones for mobile banking. Each chapter of this dissertation deals with one of these examples with the goal to draw conclusions for broader economic questions.

In the first chapter, *Crowdfunding and Demand Uncertainty*, I analyze the potential of reward-based crowdfunding to elicit demand information and improve the screening of viable projects vis-à-vis traditional external financing. Crowdfunding allows entrepreneurs to sell claims on future products directly to consumers to finance their investments. At the same time, this peer-to-peer sale of claims generates demand information that benefits the screening process for viable projects. I provide a characterization of the profit-maximizing crowdfunding mechanism when an entrepreneur knows neither the number of consumers who positively value the product nor their reservation prices. Using mechanism design theory, I show that the entrepreneur can finance all viable projects by committing to prices that decrease as the number of pledgers increases. This pricing strategy grants ex-post information rents to consumers with high reservation prices. However, if these information rents are large, then the entrepreneur prefers fixed high prices that lead to underinvestment since consumers with low valuations never participate.

The second chapter, *Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets*, is a joint project with Nikolaus Hautsch and Stefan Voigt. We analyze the potential implications of distributed ledger technologies, such as blockchain, for cross-market trading. Distributed ledgers replace trusted clearing counterparties and security depositories with time-consuming consensus protocols to record the transfer of ownership. We argue that this settlement latency exposes cross-market arbitrageurs to price risk and theoretically derive arbitrage bounds that increase with expected latency, latency uncertainty, volatility in the underlying asset, and arbitrageurs' risk aversion. We then use Bitcoin order book and network data to estimate arbitrage bounds of, on average, 121 basis points, which in fact explain 91% of the observed cross-market price differences in our sample period. Consistent with our theoretical framework, we also find that periods of high latency-implied price risk exhibit large price differences, while asset flows across exchanges chase arbitrage opportunities. Our main conclusion is that blockchain-based settlement introduces a non-trivial friction that impedes arbitrageurs' activity.

The third chapter, *Perceived Precautionary Savings Motives: Evidence from FinTech*, is coauthored with Francesco D'Acunto, Thomas Rauter, and Michael Weber. We use data from a European FinTech banking app provider to study the consumption response to the introduction of a mobile overdraft facility. In addition, we use the banking app to elicit consumers' preferences, beliefs, and motives. We find that users increase their spending permanently, lower their savings rate, and reallocate spending from non-discretionary to discretionary goods. Interestingly, users with a lot of deposits relative to their income react more than others but do not tap into negative deposits. We demonstrate that these results are not fully consistent with conventional models of financial constraints, buffer stock models, or present-bias preferences. We hence label this channel "perceived precautionary savings motives": users with a lot of liquidity behave as if they had strong precautionary savings motives even though no observables, including the elicited preferences and beliefs, suggest they should.

German Abstracts

Crowdfunding and Demand Uncertainty

Belohnungsbasiertes Crowdfunding ermöglicht Unternehmern, Forderungen auf zukünftige Produkte zu verkaufen, um Investitionen zu finanzieren und gleichzeitig Information über die Nachfrage zu generieren, die die Suche nach rentablen Projekte erleichtert. Ich charakterisiere den gewinnmaximierenden Crowdfunding-Mechanismus, wenn der Unternehmer weder die Anzahl der Konsumenten, die das Produkt positiv bewerten, noch deren Reservationspreis kennt. Der Unternehmer kann alle rentablen Projekte finanzieren, indem er sich zu Preisen verpflichtet, die mit einer wachsenden Anzahl an Unterstützern sinken. Diese Preisstrategie gewährt Konsumenten mit hohen Reservationspreisen Informationsrenten. Wenn diese Informationsrenten jedoch groß sind, dann bevorzugt der Unternehmer hohe Festpreise, die zu Unterinvestition führen.

Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets

Distributed-Ledger-Technologien ersetzen vertrauenswürdige Clearing-Gegenparteien und Sicherheitsdepots durch zeitaufwändige Konsensprotokolle, um die Eigentumsübertragung aufzuzeichnen. Diese Abwicklungslatenz setzt marktübergreifende Arbitrageure einem Preisrisiko aus. Wir leiten theoretische Arbitragegrenzen ab, die mit der erwarteten Latenz, der Latenzunsicherheit, der Volatilität und der Risikoaversion steigen. Auf Basis von Bitcoin-Orderbuch- und Netzwerkdaten schätzen wir Arbitragegrenzen von durchschnittlich 121 Basispunkten, welche 91% der beobachteten marktübergreifenden Preisunterschiede erklären. Im Einklang mit unserer Theorie weisen Perioden mit hohem latenzinduzierten Preisrisiko große Preisunterschiede auf, während Transfers von Assets Arbitragemöglichkeiten folgen. Blockchain-basierte Abwicklungen führen somit eine nicht-triviale Friktion ein, die Arbitrageaktivitäten behindert.

Perceived Precautionary Savings Motives: Evidence from FinTech

Wir untersuchen die Konsumreaktion von Erstkreditnehmern auf einen Überziehungsrahmen und erheben ihre Präferenzen, Überzeugungen und Motive durch eine FinTech-App. Die Nutzer erhöhen ihre Ausgaben dauerhaft, senken ihre Sparquote und schichten ihre Ausgaben von nicht-diskretionären auf diskretionäre Güter um. Interessanterweise reagieren liquide Nutzer mehr als andere, aber sie überziehen ihr Konto nicht. Der Überziehungsrahmen dient als eine Art Absicherung. Unsere Ergebnisse sind nicht vollständig konsistent mit Modellen der finanziellen Zwänge, Pufferbestandmodellen oder Präferenzen, die gegenwärtige Ereignisse stärker gewichten. Wir bezeichnen diesen Kanal als vermeintlich vorsorgliche Sparmotive: liquide Nutzer verhalten sich so, als hätten sie starke vorsorgliche Sparmotive, auch wenn keine Charakteristiken, einschließlich der erhobenen Präferenzen und Überzeugungen, darauf hindeuten, dass sie dies tun sollten.

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1 Crowdfunding and Demand Uncertainty

Reward-based crowdfunding allows entrepreneurs to sell claims on future products to finance investments and, at the same time, to generate demand information that benefits screening for viable projects. I provide a characterization of the profit-maximizing crowdfunding mechanism in a setting where the entrepreneur knows neither the number of consumers who positively value the product nor their reservation prices. The entrepreneur can finance all viable projects by committing to prices that decrease as the number of pledgers increase. This pricing strategy grants information rents to consumers with high reservation prices. However, if these information rents are large, then the entrepreneur prefers fixed high prices that lead to underinvestment.

1.1 Introduction

Entrepreneurs can nowadays exploit a new set of financing tools brought forth by technological innovation. Through the internet, entrepreneurs can directly contract with many individuals—the crowd—before they bear any investment costs. Reward-based crowdfunding constitutes one of the most popular types of interactions with the crowd and involves the sale of claims that holders can exchange for products after development (e.g., Kickstarter, Indiegogo). If the sale of these claims raises a prespecified amount of funds, entrepreneurs proceed to develop the product advertised in the corresponding crowdfunding campaign. In addition to serving as a financing tool, reward-based crowdfunding provides entrepreneurs with the opportunity to elicit information about product demand and to assess the viability of their projects before they enter the production phase. By committing to a price for the future product through the crowdfunding campaign, entrepreneurs may learn about the number of consumers who are willing to buy at this price.

The starting point of this paper is Strausz (2017) who models demand uncertainty as an asymmetric information problem between an entrepreneur and a group of potential consumers. In his setting, consumers either have a zero valuation of the product or a known common positive valuation, but the entrepreneur does not observe consumers' type. The entrepreneur hence faces uncertainty about how many consumers positively value the product, which I call the *market size* in this paper. Offering consumers a claim on the future product at the known common positive valuation then allows the entrepreneur to effectively learn the market size. This learning may help entrepreneurs to screen for viable projects. However, setting the right price in a crowdfunding campaign can be a challenging problem (e.g., in the case of funding a one-of-a-kind product), as consumers might possess more complex private information about their individual demand.[1]

I extend the framework of Strausz (2017) by considering uncertainty in the consumers' common private positive valuation—which I denote as the *reservation price*—in addition to uncertainty about the market size. While neither the entrepreneur nor the consumers observe the market size, consumers with a positive valuation have private information about the reservation price. This extension of demand uncertainty into market size and reservation price turns out to make a difference for the profit-maximizing crowdfunding mechanism and the potential of reward-based crowdfunding to implement first-best financing outcomes. In particular, the separation into these two components makes it necessary for the entrepreneur to condition his pricing of the crowdfunding claim on the realization of market size and thus to incentivize consumers' participation regardless of their reservation price.

I set up a parsimonious contracting game as a simple one-shot sale of a claim on the future product to privately informed consumers but abstract from any issues related to moral hazard.[2] The entrepreneur is penniless and aims to raise funds for the idea she wishes to implement at some fixed investment cost. Due to the asymmetric information problem vis-à-vis consumers, contracting with uninformed outside investors to raise the investment cost leads to underinvestment, since some ex-post viable projects do not receive funding, or overinvestment, as ex-post unprofitable projects get funded. However, direct contracting with informed consumers generates valuable information

[1] For instance, The Economist (2010) reports the example of a book publisher who finances the republication of a sold-out book via crowdfunding and his efforts to tease out consumers' price sensitivity.

[2] See Strausz (2017) and Chemla and Tinn (2019) for papers that study the interaction of crowdfunding and entrepreneurial moral hazard.

for the screening process of the entrepreneur.[3] I first illustrate the key tensions that arise in this setting using an intuitive structure of a crowdfunding campaign and then corroborate the findings with mechanism design.

The intuitive reward-based crowdfunding campaign comprises a price for a claim on the future product and a funding target that the entrepreneur posts on a public platform. Based on the information provided in the campaign, consumers decide whether to pledge funds in exchange for a claim on the future product or not. The entrepreneur only enters production if the total pledges exceed a pre-specified target level.[4] As a result, the funding target serves as a tool to condition the entrepreneur's participation on the viability of the venture, given the observed demand at the posted price. This scheme successfully elicits the number of consumers who are willing to buy a claim on the product at a given price.

I consider four demand states which are the result of combinations of large and small market sizes and high and low reservation prices, respectively. If the project is only viable for the high reservation price, then the entrepreneur effectively faces uncertainty about whether the market size at this price is sufficiently large, as shown in Strausz (2017). Setting the price to the high reservation price (and the funding target to cover all production costs at this price) allows the entrepreneur to learn the market size for this price and finance all viable projects. If the project is only viable at a specific market size but for different reservation prices, then the entrepreneur optimally chooses the price that maximizes expected profits. Even if setting the price to the low reservation price implements first-best financing outcomes (given that production at the low price is feasible), the entrepreneur might find it optimal to choose the high price that yields higher expected profits but does not lead to financing if consumers have low reservation prices.

If demand states with different combinations of reservation prices and market sizes yield positive profits, then the choice of a fixed price does not lead to financing in one demand state with positive profits. Suppose the demand states with (i) a high reser-

[3] I abstract from any private information that the entrepreneur may have. For instance, Chakraborty and Swinney (2019) consider an entrepreneur who is privately informed about product quality and may use the crowdfunding campaign as a signal vis-à-vis potential backers. Similarly, Nan et al. (2019) consider an entrepreneur who is privately informed about her implementation costs.

[4] Platforms that focus on for-profit projects (e.g., Kickstarter) commonly use all-or-nothing crowdfunding schemes, while other platforms allow entrepreneurs to keep what they raise, even if the campaign does not reach the target. Other crowdfunding platforms (e.g., Indiegogo) allow entrepreneurs to choose between using the all-or-nothing or the keep-what-you-raise model (Cumming et al., 2019). In this paper, only all-or-nothing schemes emerge as the entrepreneur's preferred choice and I refer to Chang (2019) for a comparison to the keep-what-you-raise scheme.

vation price and a small market size, (ii) a low reservation price and a large market size and (iii) a high reservation price and a large market size all yield positive profits. Setting the price to the low reservation price does not lead to successful financing in state (i), while setting the price to the high reservation price does not finance state (ii), even though both demand states are profitable. To finance both demand states using the same crowdfunding campaign, the entrepreneur has to commit to a price schedule that depends on the number of consumers who participate in the campaign, that is, charge a low price if there are many pledgers and charge a high price if there are only few pledgers. The entrepreneur has to take the strategic behavior of consumers who maximize their expected utility into account. In particular, consumers with high reservation prices want to buy the product at a low price. However, the entrepreneur may exploit the uncertainty about the market size to incentivize consumers' truthful behavior and thus finance all viable projects. This pricing scheme requires that consumers with low reservation prices always pay the low price, while consumers with high reservation prices are expected to pay the high price if the market size is small but the low price if the market size is large. In this way, the entrepreneur promises consumers with high reservation prices an information rent in the demand state where market size is large but extracts all surplus from consumers with low reservation prices. This state-contingent price commitment is incentive-compatible and leads to financing in all three demand states (i), (ii) and (iii).

Even though a price commitment that implements first-best financing outcomes always exists in my model, the entrepreneur might prefer another strategy. Instead of giving up some surplus in state (iii) (where both reservation prices and market size are high), the entrepreneur may just choose the high price for her campaign and extract the full surplus in states (i) and (iii). This strategy may yield higher expected profits than the state-contingent price commitment under some parameter constellations. Just as in traditional models of monopolistic competition, profit maximization might hence interfere with the provision of first-best financing outcomes.

To corroborate the findings of the intuitive crowdfunding campaign, I employ a mechanism design approach. Mechanism design allows me to characterize the profit-maximizing reward-based crowdfunding mechanism and necessary conditions for the existence of a mechanism that implements first-best allocations. The resulting profit-maximizing mechanism explicitly takes the incentive compatibility and participation constraints of individual consumers into account. I first demonstrate that there exists a direct mechanism which implements an equilibrium in which the entrepreneur extracts the full surplus—a common result in settings where consumers have quasi-linear preferences and correlated valuations (e.g., Myerson, 1981; Crémer and McLean, 1985). However, depending on consumers' beliefs, there is a large number of other equilibria in which either consumers collectively misreport their valuation or some consumers misreport and no production takes place under the full-surplus extraction mechanism. Collective misreporting in fact yields higher expected utility for consumers with high valuations. Following the robust implementation refinement (e.g., Bergemann and Morris, 2009, 2011), I thus require a mechanism to be belief-robust in the sense that it only implements equilibria in which it is optimal for consumers to report truthfully, regardless of their beliefs about other consumers' behavior.

The belief-robust profit-maximizing crowdfunding mechanism does in general not extract the full surplus for the entrepreneur, since there are parameter constellations where the entrepreneur either has to grant consumers with high valuations an information rent (to guarantee their truthful behavior) or she decides not to produce for consumers with low valuations and extracts only the surplus of consumers with high valuations. Intuitively, the entrepreneur faces a trade-off and has to decide whether to only produce for consumers with high valuations, which leads to forgone profits when consumers have low valuations, and to grant consumers with high valuations an information rent, which leads to forgone profits when consumers have high valuations. Moreover, the belief-robust profit-maximizing crowdfunding mechanism implements first-best allocations only if the demand state that the entrepreneur is able to finance by setting a low price compensates her for the forgone expected profits of setting a high price. These results hence exactly mirror the findings of the intuitive crowdfunding campaign.

My theoretical results echo Harris and Raviv (1981) who analyze the problem of a monopolist facing asymmetric information about consumer valuations. In their framework, the monopolist chooses some form of priority pricing scheme if she faces capacity constraints. Just as in any (multi-unit) auction setting, the supply restriction helps to incentivize consumers' information revelation (e.g., Maskin and Riley, 1989). However, if the production capacity exceeds potential demand, then the absence of scarcity does not allow the monopolist to discriminate across consumers based on the probability of receiving the product. Harris and Raviv (1981) show that the monopolist optimally prefers to sell products at a fixed price in this case. The crowdfunding game of my paper is similar to a setting with monopolists facing demand uncertainty (e.g., Sandmo, 1971; Leland, 1972; Weitzmann, 1974; Klemperer and Meyer, 1986), since the implicit assumption is that the entrepreneur has an idea for an innovative product which grants (at least local) monopoly power. However, the crowdfunding entrepreneur faces a temporal separation between the sale of claims on the future product and the corresponding production decisions. In addition to her participation, the crowdfunding entrepreneur may hence also condition the pricing of the product on the outcome of the crowdfunding campaign and share some rents with consumers to finance projects in different demand states.

The derivation of the profit-maximizing mechanism rests on the assumption that the entrepreneur can commit to a pricing strategy. Upon observing consumers' reservation prices, the entrepreneur might have an incentive to charge the maximum possible price ex-post. However, consumers with high valuations anticipate this deviation and might refrain from sending truthful reports altogether, which in turn hampers the entrepreneur's incentives to change the initially proposed pricing. Similarly, if the entrepreneur does not commit to deliver the product to consumers after a successful crowdfunding campaign and rather seeks bank financing with the newly acquired demand information, she reduces the consumers' incentives to truthfully report their valuation. Moreover, just as in the durable goods literature (e.g., Coase, 1972; Stokey, 1981; Bulow, 1982; Gul et al., 1986), the entrepreneur might also have an incentive to charge different prices to consumers on the market after crowdfunding than to consumers who participate in the crowdfunding campaign. Albeit outside of my framework, charging lower prices on the secondary market might incentivize consumers with high valuations to wait for the market after crowdfunding rather than reporting high valuations. This type of time-consistency problem of the entrepreneur might thus hamper the screening benefits of crowdfunding.

In practice, crowdfunding platforms act as intermediaries between entrepreneurs and consumers. These platforms collect the funds of consumers at the time they decide to contribute to a campaign, rather than collecting reported valuations or commitments to buy at a state-contingent price that unravels in the future. Entrepreneurs, on the other hand, may typically either specify the full menu of rewards and corresponding fixed prices at the campaign launch or add new rewards at different fixed prices at a later stage. The crowdfunding platform transfers the funds to entrepreneurs only if the funding goal is achieved and hence effectively serves as a commitment device for the entrepreneurs' pricing strategy. These restrictions also imply that a direct replication of the state-contingent pricing rule where each consumer's contribution decreases as the number of pledgers increase cannot be found in practice. However, the prices of each reward are typically minimum pledge amounts which allows consumers to voluntarily contribute funds in excess of the posted prices. Moreover, by design of the crowdfunding platform, consumers typically may change their pledge amount or choose a different reward during the lifetime of a campaign. Although dynamic considerations are outside of my model, these tools allow me to sketch an indirect replication of the state-contingent pricing mechanism. For instance, an entrepreneur may launch the campaign with low prices and contact consumers directly to ask for higher contributions in case of a small number of pledgers towards the campaign end. The entrepreneur may also add an additional reward where she offers essentially the same product but at a higher price.[5] Consumers may then increase their pledge amount or upgrade to a new reward category, thereby ensuring the campaign's viability. If consumers refuse to do so, they effectively reveal that they do not value the product high enough.

Lastly, I briefly discuss the relation between the profit-maximizing reward-based mechanism to security-based crowdfunding (e.g., Li, 2016; Brown and Davies, 2018; Terovitis, 2019). Although an explicit modeling of the security design problem is also outside of my framework, I can interpret reward-based crowdfunding as a debt-like contract where the entrepreneur borrows a pre-specified amount from each consumer in exchange for a fixed repayment promise (either in the form of the future product or by returning the funds if the campaign is unsuccessful). The state-contingent pricing rule then resembles a combination of a debt contract that all consumers buy and a credit line that consumers with high reservation prices offer the entrepreneur. The credit line contract specifies that the entrepreneur only draws on it if the campaign features a small number of pledgers but may not do so in case of a large market size. Together, these two securities replicate the utility and cash flows of the state-contingent crowdfunding mechanism.

Overall, my paper contributes to the theoretical literature on crowdfunding by distinguishing between market size and reservation prices. For instance, Strausz (2017) and Chemla and Tinn (2019) consider binary consumer valuations. In their setting, demand uncertainty effectively boils down to uncertainty about the market size which can be resolved by setting the price of the crowdfunding claim equal to the only possible positive reservation price. In my setting, the entrepreneur faces two possible reservation prices and might exploit the uncertainty in the market size to incentivize

[5]In practice, entrepreneurs offer slightly differentiated products at different prices. However, I do not explicitly consider product differentiation in my model.

consumers' truthful behavior. By contrast, Ellman and Hurkens (2019) consider positive private consumer valuations that are either high or low, but for a given market size. Their main focus is price discrimination across consumers with different positive valuations, while in my setting consumers either have low or high valuations, but there are never two consumers with a high and a low valuation at the same time. I thus focus on consumer participation and information revelation rather than price discrimination.

1.2 A Model of Crowdfunding

In this section, I build a model of investment with demand uncertainty in the spirit of Strausz (2017). The model considers an entrepreneur who, prior to her investment decision, directly interacts with an uncertain number of consumers who are privately informed about their common reservation price, to elicit information about product demand. The model has two stages: the entrepreneur raises funds to finance some fixed investment costs in the first stage; production takes place and payoffs realize in the second stage.

I consider a penniless entrepreneur with an idea for a product which requires a fixed investment $I > 0$. I assume that the entrepreneur is crucial for the success of the venture and cannot sell her idea to outsiders. After development, the entrepreneur can produce the product at constant marginal cost $c > 0$. The entrepreneur maximizes expected profits.

The economy is populated by n consumers who are privately informed about their common reservation price of the product. Consumers have unit demand for the product in the sense that they only get utility for exactly one unit of the product. I assume that consumers have a private valuation v of one unit of the product. Consumers share a common valuation, but they do not know how many other consumers also have the same reservation price. Each consumer has additively separable utility, is risk neutral and maximizes expected utility subject to her individual rationality constraint of getting non-negative expected utility.

While consumers have private information about v, I assume that the entrepreneur faces demand for the product that is uncertain in two dimensions: how many consumers value the product—the *market size* n—and consumers' willingness to pay for the product if they value the product—the *reservation price* v. From the perspective of the entrepreneur, $\tilde{n}$ and $\tilde{v}$ denote the random variables associated with realizations n and v, respectively.

The entrepreneur has subjective probability distributions over possible values of $\tilde{n}$ and $\tilde{v}$. Consumers also face uncertainty about $\tilde{n}$ and share the corresponding subjective probability distribution of the entrepreneur. In particular, the entrepreneur and the consumers believe that $\tilde{n}$ is either n_H with probability π_n or $n_L < n_H$ with probability $1 - \pi_n$. Similarly, the entrepreneur believes that $\tilde{v}$ is either v_H with probability π_v or $v_L < v_H$ with probability $1 - \pi_v$. Moreover, I assume that $\tilde{n}$ and $\tilde{v}$ are stochastically independent, and I rule out cases where marginal costs exceed possible reservation prices by assuming $c < v_L$ (since the entrepreneur would not find it worthwhile to produce in this case anyway).

Therefore, the model features four possible states of aggregate demand $(\tilde{n}, \tilde{v})$: (i) (n_L, v_L) with probability $\pi_{LL} \equiv (1 - \pi_n)(1 - \pi_v)$, (ii) (n_L, v_H) with probability $\pi_{LH} \equiv (1 - \pi_n)\pi_v$, (iii) (n_H, v_L) with probability $\pi_{HL} \equiv \pi_n(1 - \pi_v)$, and (iv) (n_H, v_H) with probability $\pi_{HH} \equiv \pi_n \pi_v$. Expected aggregate demand is hence given by

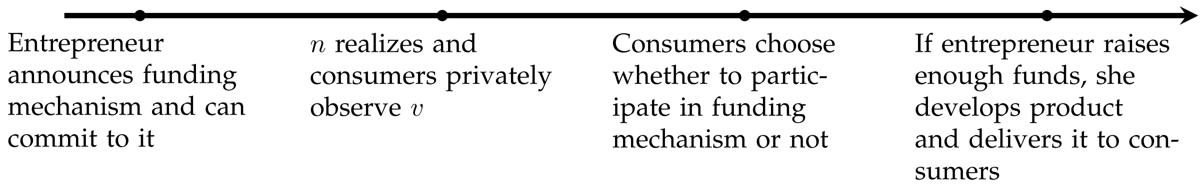
$$\mathbb{E}[\tilde{n}\tilde{v}] = \sum_{\substack{i \in \{L,H\} \\ j \in \{L,H\}}} \pi_{ij} n_i v_j. \tag{1.1}$$

The timeline of the model is as follows: Before the game begins, the entrepreneur announces her strategy—the *crowdfunding mechanism*—and can commit to it. Once the entrepreneur has committed to a game and a strategy, consumers choose their own strategy for the game. More specifically, consumers first privately observe their valuations v (but they do not observe n) and then choose whether to participate in the crowdfunding mechanism or not. If the entrepreneur successfully raises enough funds to develop the product, she delivers it to the consumers at the price specified in the crowdfunding mechanism in the next stage, while incurring marginal cost c for each unit produced. After this stage, all payoffs realize and the game ends. Figure 1.1 summarizes the timeline of this game.

1.2.1 First-Best Benchmark

As a benchmark, I use the case of perfect information where the entrepreneur can observe the number of consumers n and their reservation prices v once the game begins. Therefore, she can condition her investment decision on both demand parameters. In

Figure 1.1: Timeline of the Crowdfunding Game



Notes: This figure illustrates the timeline of the crowdfunding game. The entrepreneur announces a funding mechanism at the beginning of the game to initialize the funding stage. Next, consumers privately observe their valuations and choose whether to participate in the funding mechanism proposed by the entrepreneur. After the consumers' participation decision, the funding stage concludes and the entrepreneur evaluates the proceeds. If the entrepreneur raises sufficient funds, the production stage begins where the entrepreneur delivers the product to consumers.

this full-information benchmark, the entrepreneur maximizes profits by producing a total quantity n that she sells for v.

It is optimal for the entrepreneur to invest only if the project's revenue covers the total production costs, that is, if

$$nv \geq I + nc, \tag{1.2}$$

and to do nothing otherwise. With perfect information, the project generates an ex-ante expected aggregate net surplus of

$$S^* \equiv \sum_{\substack{i\in\{L,H\} \\ j\in\{L,H\}}} \pi_{ij} \left[n_i(v_j - c) - I\right] \cdot \mathbb{1}_{\{n_i(v_j-c)-I\geq 0\}}. \tag{1.3}$$

The entrepreneur achieves the first-best funding outcome as all demand states with positive profits are funded and no project with negative profits gets funding. A funding mechanism is hence efficient and implements first-best financing outcomes if it finances all projects for which the realized demand state (n, v) satisfies Equation (1.2).

Throughout the paper, I only consider projects that are worthwhile with positive probability, that is, I assume $S^* > 0$. Put differently, at least one of the four demand states yields positive profits. Given the four possible states of aggregate demand and assuming that state (n_L, v_L) never yields positive profits, the aggregate net surplus can exhibit four different scenarios:

(a) Only state (n_H, v_H) yields positive profits, that is, the expected surplus is

$$S^*_{(a)} = \pi_{HH} \left[n_H(v_H - c) - I \right]. \tag{1.4}$$

(b) Only states (n_H, v_H) and (n_L, v_H) yield positive profits, that is,

$$S^*_{(b)} = \pi_{HH} \left[n_H(v_H - c) - I \right] + \pi_{LH} \left[n_L(v_H - c) - I \right]. \tag{1.5}$$

(c) Only states (n_H, v_H) and (n_H, v_L) yield positive profits, that is,

$$S^*_{(c)} = \pi_{HH} \left[n_H(v_H - c) - I \right] + \pi_{HL} \left[n_H(v_L - c) - I \right]. \tag{1.6}$$

(d) The states (n_H, v_H), (n_L, v_H) and (n_H, v_L) yield positive profits, that is,

$$S^*_{(d)} = \pi_{HH} \left[n_H(v_H - c) - I \right] + \pi_{LH} \left[n_L(v_H - c) - I \right] + \pi_{HL} \left[n_H(v_L - c) - I \right]. \tag{1.7}$$

Figure 1.2 visualizes the four different scenarios.

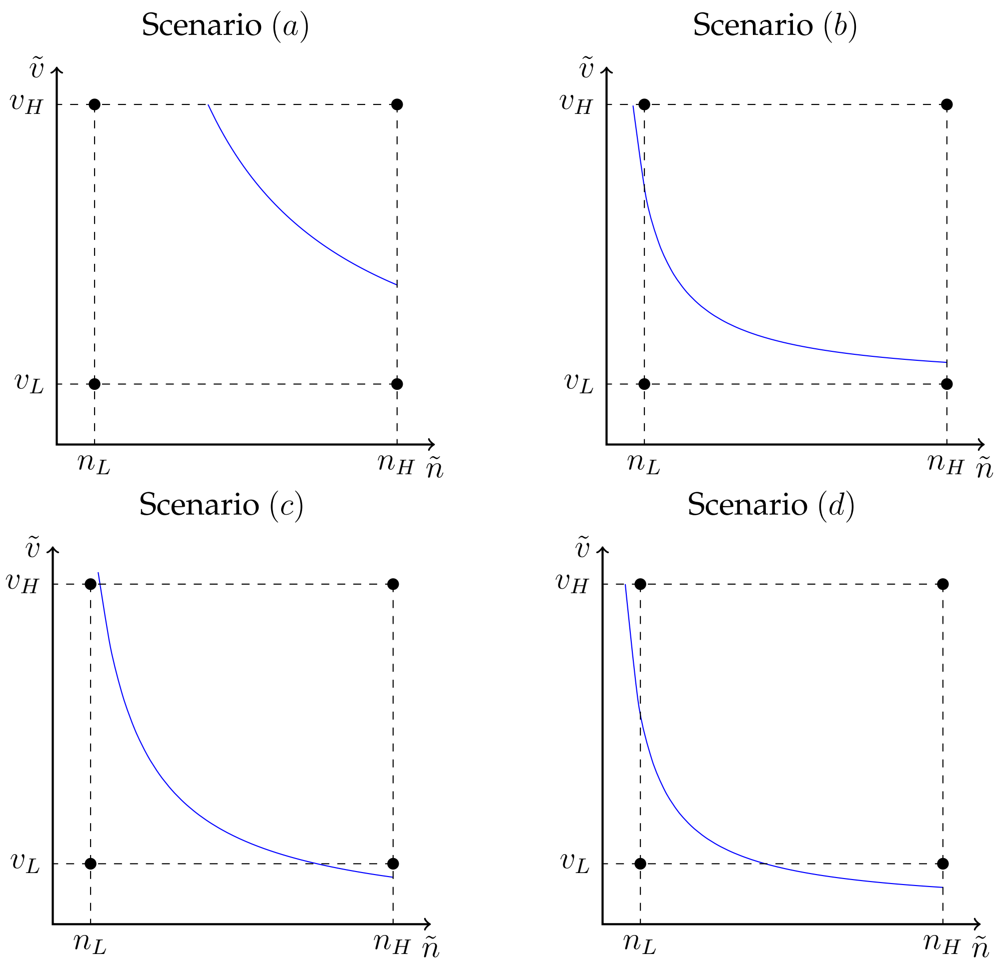
As shown in Strausz (2017), the availability of a competitive credit market that is willing to provide I allows the entrepreneur to implement all viable projects and extract the full surplus. However, once the entrepreneur does not observe the demand state, competitive lenders are not sufficient for a first-best funding outcome anymore.

1.2.2 Investing with Demand Uncertainty

Before I turn to crowdfunding, I demonstrate that financing through uninformed outside lenders might lead to over- or underinvestment and does not achieve the first-best funding outcome in all possible demand states.

Consider the setting where the entrepreneur must decide to invest I without knowing $\tilde{n}$ or $\tilde{v}$, but she learns the realizations after investment. Moreover, suppose the entrepreneur can raise I from competitive outside financiers (e.g., banks or venture capitalists) and that these outside financiers do not possess any superior information about demand vis-à-vis the entrepreneur. The entrepreneur's expected profits from

Figure 1.2: Illustration of the First-Best Benchmark



Notes: This figure illustrates the different scenarios of first-best funding outcomes. The solid line corresponds to the curve where realized demand (n, v) exactly covers the total production costs, that is, $nv = I + nc$. Demand states above the solid line yield positive profits, while states below yield negative profits.

investing are in this case

$$\bar{\Pi} \equiv \sum_{\substack{i \in \{L,H\} \\ j \in \{L,H\}}} \pi_{ij} \left[n_i (v_j - c) \right] - I. \tag{1.8}$$

It is only profitable for the entrepreneur to invest if $\bar{\Pi} \geq 0$. However, the decision of the entrepreneur to invest might lead to either under- or overinvestment. For viable projects, the realizations of n and v have to satisfy Equation (1.2), but there might be parameter constellations such that $\bar{\Pi} < 0$ and the entrepreneur does not invest. However, in this case, underinvestment relative to the first-best benchmark results because the entrepreneur does not produce for any realization (n, v) where it would be nonetheless efficient to produce. Similarly, for parameter constellations such that $\bar{\Pi} \geq 0$, the entrepreneur does invest I, but her decision implies overinvestment because she produces even when aggregate demand turns out to be insufficient to cover total costs.

1.2.3 Reward-Based Crowdfunding

Strausz (2017) shows that the all-or-nothing, reward-based crowdfunding scheme with a fixed price can elicit demand information such that the entrepreneur finances all viable projects in a setting where reservation prices can take only one value. In this scheme, the entrepreneur offers consumers the opportunity to pledge funds in exchange for the product in the future as a *reward*, but only if the entrepreneur raises enough funds to finance overall production. If consumers do not pledge a sufficient amount of funds, then the entrepreneur does not receive anything and the funding stage fails.

Formally, the entrepreneur offers a contract that consists of a price p and a target τ_p. I call the contract $\{p, \tau_p\}$ *crowdfunding campaign*, which states that the entrepreneur only invests if the total number of pledgers $n(p)$ for a given price p provide sufficient funds to cover the target τ_p. If the total amount of pledges falls short of τ_p, then the entrepreneur does not obtain any funds, and she neither invests nor produces. The participation of consumers in the crowdfunding campaign is voluntary and yields the expected utility

$$\mathbb{E}\left[u(p, \tau_p | v)\right] = \sum_{\substack{i \in \{L,H\} \\ j \in \{L,H\}}} \pi_{ij}(v - p) \cdot \mathbb{1}_{\{n(p)p \geq \tau_p\}}, \tag{1.9}$$

to a consumer with valuation v, where $n(p)$ refers to the number of consumers who pledge funds at price p. In fact, for any price $p \in [0, v]$, exactly n consumers find it optimal to pledge p, whereas no consumer pledges funds for $p > v$. The entrepreneur's expected profits of the crowdfunding campaign become

$$\mathbb{E}\left[\Pi(p, \tau_p)\right] = \sum_{\substack{i \in \{L,H\} \\ j \in \{L,H\}}} \pi_{ij}\left[n_i(p - c) - I\right] \cdot \mathbb{1}_{\{v_j \geq p\}} \cdot \mathbb{1}_{\{n_i p \geq \tau_p\}}. \tag{1.10}$$

The price commitment p serves as a tool to elicit information about the unknown number of consumers $\tilde{n}$ who are willing to participate at this price. The funding target τ_p, on the other hand, serves as a tool to condition the entrepreneur's investment decision on the viability of the project. In that sense, the funding target grants the entrepreneur a right to revoke the promise of delivering the product to consumers at the committed price in case the project turns out to be unprofitable.

Since it is always optimal for the entrepreneur to produce if $np \geq nc + I$, a funding target of $\tau_p = pI/(p - c)$ ensures that the campaign raises enough funds to cover all costs if the venture enters the production stage. The funding target hence reflects the entrepreneur's choice of p. In fact, the entrepreneur has no incentive to pick any other funding goal than $pI/(p - c)$. Expected profits of the entrepreneur simplify to

$$\mathbb{E}\left[\Pi(p)\right] = \sum_{\substack{i\in\{L,H\} \\ j\in\{L,H\}}} \pi_{ij}\left[n_i(p-c) - I\right] \cdot \mathbb{1}_{\{v_j \geq p\}} \cdot \mathbb{1}_{\{n_i(p-c)-I\geq 0\}}. \tag{1.11}$$

If the campaign is successful, each consumer pays price p but might have a higher private reservation price for the product. Given the funding mechanism and his private reservation price, each consumer receives expected utility

$$\begin{aligned} \mathbb{E}\left[u(p|v)\right] = \pi_n(v-p) \cdot \mathbb{1}_{\{v\geq p\}} \cdot \mathbb{1}_{\{n_H(p-c)-I\geq 0\}} \\ + (1-\pi_n)(v-p) \cdot \mathbb{1}_{\{v\geq p\}} \cdot \mathbb{1}_{\{n_L(p-c)-I\geq 0\}}, \end{aligned} \tag{1.12}$$

Total ex-ante expected consumer surplus is thus given by

$$\mathbb{E}\left[\tilde{n}u(p|\tilde{v})\right] = \sum_{\substack{i\in\{L,H\} \\ j\in\{L,H\}}} \pi_{ij}\left[n_i(v_j - p)\right] \cdot \mathbb{1}_{\{v_j \geq p\}} \cdot \mathbb{1}_{\{n_i(p-c)-I\geq 0\}}. \tag{1.13}$$

If the entrepreneur knew consumers' reservation price at the beginning of the game, she would optimally set $p = v$ in the crowdfunding campaign and leave the consumers without any surplus. However, due to the uncertainty in v, this is in general not possible.

If only one of the two possible reservation prices leads to positive profits, then the entrepreneur effectively only faces uncertainty about the market size. Both in scenario (a) (where (n_H, v_H) is the only profitable demand state) and scenario (b) (where also (n_L, v_H) is profitable), the entrepreneur can optimally set the price $p = v_H$ to maximize expected profits and extract the full surplus. The entrepreneur thereby effectively avoids projects where consumers have a low reservation price v_L since these demand states are unprofitable anyway. Even though reservation prices are unknown, the viability constraint ensures that the entrepreneur discards the project for demand states with the low reservation price.

If both high and low reservation prices are associated with positive profits, the entrepreneur may choose between setting the price to v_L or v_H. The uncertainty in reservation prices might now lead to a discrepancy between profit and surplus maximization. To see this, consider scenario (c) with total surplus $S^*_{(c)} = \pi_{HH} [n_H(v_H - c) - I] + \pi_{HL} [n_H(v_L - c) - I]$. Only a price $p = v_L$ ensures that all viable projects get funded and the respective expected surpluses become

$$\mathbb{E}_{(c)} [\Pi(v_L)] = (\pi_{HH} + \pi_{HL}) [n_H(v_L - c) - I] \tag{1.14}$$

$$\mathbb{E}_{(c)} [\tilde{n}u(p|\tilde{v})] = \pi_{HH} n_H (v_H - v_L), \tag{1.15}$$

which together amount to $S^*_{(c)}$. In this case, consumers receive an information rent as the entrepreneur cedes part of the high potential profits of demand state (n_H, v_H) to consumers. For a price $p = v_H$, the demand state (n_H, v_L) does not receive financing although it is profitable. Just as in standard models of monopolistic competition where the monopolist does not charge the socially optimal price, the crowdfunding entrepreneur in my model might not find it optimal to choose the price that implements first-best financing outcomes. Due to the specific valuation structure of my model, a profit-maximizing entrepreneur would weigh whether to set $p = v_L$ or $p = v_H$ and only set the first-best price $p = v_L$ if the corresponding expected profits are higher, that is, if

$$\mathbb{E}_{(c)} [\Pi(v_L)] > \mathbb{E}_{(c)} [\Pi(v_H)] \quad \Leftrightarrow \quad (1 - \pi_v) [n_H(v_L - c) - I] > \pi_v n_H (v_H - v_L). \tag{1.16}$$

The above condition states that the expected profits in state (n_H, v_L) must exceed the expected forgone profits of state (n_H, v_H). Therefore, depending on parameter constellations, the entrepreneur optimally commits to the first-best funding outcome which is characterized by profit maximization and positive consumer surplus such that the total surplus is maximized. However, there also exists a scenario in which the entrepreneur's choice of p leaves the consumers without any surplus and underinvestment results.

However, uncertainty in reservation prices might also lead to a failure of the existence of a fixed price that implements first-best financing outcomes. Consider scenario (d) with profitable demand states (n_H, v_H), (n_L, v_H) and (n_H, v_L). Setting the price $p = v_H$ does not lead to a successful campaign in state (n_H, v_L), while setting the price $p = v_L$ does not lead to financing in state (n_L, v_H). Under unknown market size and unknown reservation prices, there does not exist a fixed-price, all-or-nothing, reward-based crowdfunding scheme that achieves the first-best funding outcome in all demand states.

The only way to ensure that all viable projects get funded through a reward-based crowdfunding campaign is to introduce *state-contingent prices*, that is, the entrepreneur needs to charge v_L if $n = n_H$ and v_H if $n = n_L$ to finance all viable projects. However, the entrepreneur has to take the strategic behavior of consumers, who might be reluctant to act according to their true valuation, into account. In particular, consumers with high reservation prices v_H might behave as if they have a low reservation price v_L and pocket the information rent $v_H - v_L$. Let $\hat{p} = (p_{HH}, p_{HL}, p_{LH})$ be the vector of state-contingent prices where p_{ij} denotes the price the entrepreneur charges if n_i consumers are willing to buy the product at v_j.[6] Consumers' incentive compatibility constraints to behave truthfully are for the consumers with valuation v_L

$$\underbrace{\pi_n(v_L - p_{HL})}_{\text{all } v_L\text{-consumers behave truthfully}} \geq \underbrace{\pi_n(v_L - p_{HH}) + (1 - \pi_n)(v_L - p_{LH})}_{\text{all } v_L\text{-consumers behave as } v_H\text{-consumers}} \tag{1.17}$$

and for the consumers with valuation v_H

$$\underbrace{\pi_n(v_H - p_{HH}) + (1 - \pi_n)(v_H - p_{LH})}_{\text{all } v_H\text{-consumers behave truthfully}} \geq \underbrace{\pi_n(v_L - p_{LH}).}_{\text{all } v_H\text{-consumers behave as } v_L\text{-consumers}} \tag{1.18}$$

Solving these constraints yields $\hat{p} = (v_L, v_L, v_H)$ and ensures that all consumers behave according to their true reservation price. To derive the corresponding pricing rule, recall that $n(p)$ denotes the number of consumers who are interested to buy at price p, and suppose that the entrepreneur is able to collect consumers' demand at different prices. Due to unit demand, a consumer's demand is either zero or one for v_L and either zero or one for v_H. Clearly, if a consumer is willing to buy at the high price, then he also wants to buy at the low price. Denote the market size at the high and low price

[6] The entrepreneur does not need to specify p_{LL} since she does not produce in this demand state anyway.

as $n(v_H)$ and $n(v_L)$, respectively, with $n(v_L) \geq n(v_H)$. A pricing rule of the form

$$p^* \equiv \begin{cases} v_L \text{ if } n(v_L) = n_H \text{ or } n(v_H) = n_H \\ v_H \text{ if } n(v_H) = n_L \end{cases} \tag{1.19}$$

achieves first-best funding outcomes with the respective surpluses

$$\mathbb{E}_{(d)}\left[\Pi(p^*)\right] = (\pi_{HH} + \pi_{HL})\left[n_H(v_L - c) - I\right] + \pi_{LH}\left[n_L(v_H - c) - I\right] \tag{1.20}$$

$$\mathbb{E}_{(d)}\left[\tilde{n}u(p^*|\tilde{v})\right] = \pi_{HH} n_H (v_H - v_L), \tag{1.21}$$

and

$$\mathbb{E}_{(d)}\left[\Pi(p^*)\right] + \mathbb{E}_{(d)}\left[\tilde{n}u(p^*|\tilde{v})\right] = S^*_{(d)}. \tag{1.22}$$

Given the entrepreneur's pricing in Equation (1.19), consumers find it optimal to participate. A consumer with reservation price v_L receives expected utility

$$\mathbb{E}\left[u(p^*|v_L)\right] = \pi_n(v_L - v_L) = 0, \tag{1.23}$$

while a consumer with reservation price v_H gets expected utility

$$\mathbb{E}\left[u(p^*|v_H)\right] = \pi_n(v_H - v_L) + (1 - \pi_n)(v_H - v_H) = \pi_n(v_H - v_L), \tag{1.24}$$

which ensures that he always behaves truthfully. As I demonstrate in the mechanism design setup, consumers with a high reservation price require this information rent to always truthfully report their valuation and allow the entrepreneur to implement the first-best financing outcome.

However, the entrepreneur might again get higher expected profits from following a strategy that deviates from the pricing scheme that implements first-best financing outcomes. The entrepreneur only proposes the state-contingent pricing rule if

$$\mathbb{E}_{(d)}\left[\Pi(p^*)\right] > \max\left\{\mathbb{E}_{(d)}\left[\Pi(v_L)\right], \mathbb{E}_{(d)}\left[\Pi(v_H)\right]\right\}, \tag{1.25}$$

which is again the case whenever

$$(1 - \pi_v)\left[n_H(v_L - c) - I\right] > \pi_v n_H\left(v_H - v_L\right). \tag{1.26}$$

If state (n_H, n_L) compensates for the forgone expected profits of state (n_H, v_H), then the entrepreneur optimally chooses the first-best pricing strategy with state-contingent prices. Otherwise, the entrepreneur optimally chooses the fixed-price scheme $p = v_H$.

As the current setting follows a rather intuitive approach, I embed the above problem in a more general mechanism design setup in the following section. As it turns out, the above considerations in fact constitute the entrepreneur's profit-maximizing strategy if she wants to ensure that consumers report truthfully, regardless of their beliefs about other consumers' behavior.

1.3 Optimal Crowdfunding Mechanism

In this section, I explicitly model individual consumers' incentive and participation constraints and show that the considerations from the previous section arise in a general mechanism design setup. To cast the crowdfunding problem in a framework of mechanism design, I closely follow Strausz (2017) (but abstract from moral hazard and private cost information on the entrepreneur's side) and incorporate a more complex valuation structure into his setting by considering valuations that are drawn from one of two possible binary distributions. I first define the design problem and relevant constraints for potential mechanisms and then characterize the profit-maximizing crowdfunding scheme.

1.3.1 Crowdfunding Design Problem

A crowdfunding mechanism seeks to implement an allocation between the penniless entrepreneur and N consumers, where I denote a generic consumer by $k \in \mathcal{N} \equiv \{1, ..., N\}$. An *allocation* involves monetary transfers from the consumers to the entrepreneur, an investment decision and consumer-specific production decisions of the entrepreneur. I denote the transfer from consumer k to the entrepreneur by t_k. The allocation also describes whether the entrepreneur invests, $x_0 = 1$, or not, $x_0 = 0$, and whether the entrepreneur produces for consumer k, $x_k = 1$, or not, $x_k = 0$. If the entrepreneur does not invest, then $x_k = 0$ for all $k \in \mathcal{N}$. Thus, an allocation is a vector $\mathbf{a} = (\mathbf{t}, \mathbf{x})$ where $\mathbf{t} = (t_1, ..., t_N) \in \mathcal{T} \equiv \mathbb{R}^N$ are transfers and $\mathbf{x} = (x_0, ..., x_N) \in \mathcal{X} \equiv \{0, 1\}^{N+1}$ are outputs. I denote the set of possible allocations as $\mathcal{A} \equiv \mathcal{T} \times \mathcal{X}$.

Since the entrepreneur does not have any funds, an allocation cannot involve any net positive transfers to the consumers before investment and the transfers of consumers must be sufficient to cover the fixed investment costs $I > 0$ and the constant marginal costs $c > 0$ associated with production decisions. An allocation is hence *feasible* if the transfers from the consumers cover the total production costs, that is, if

$$\sum_{k \in \mathcal{N}} t_k \geq I x_0 + c \sum_{k \in \mathcal{N}} x_k. \tag{1.27}$$

Each consumer has quasilinear preferences with unit demand and private valuation v_k. The private valuation is either zero or $v > 0$. The entrepreneur neither observes the magnitude of the positive valuation v nor the number of consumers with a positive valuation $n > 0$, but she knows the set of possible realizations and has a subjective probability distribution over these possible realizations. Nature draws individual consumer valuations where n consumers get a positive valuation and $N - n$ consumers get a zero valuation. The number of consumers with a positive valuation is either $n = n_H$ with probability π_n or $n = n_L < n_H$ with probability $1 - \pi_n$. For these n consumers, the positive valuation is either $v = v_H$ with probability π_v or $v = v_L$, where $v_L \in (c, v_H)$, with probability $1 - \pi_v$. The remaining $N - n$ consumers have a zero valuation of the product. The vector of individual valuations $\mathbf{v} = (v_1, ...v_N) \in \mathcal{V} \equiv \{0, v\}^N$ therefore contains $N - n$ elements that are zero and n elements that are either v_H or v_L. Let $\pi(\mathbf{v})$ be the corresponding probability of the state of valuations $\mathbf{v}$.

Just as the entrepreneur does not know the realized state of valuations $\mathbf{v}$, each consumer is only informed about his own valuation. Thus, a consumer k knows v_k but does not know how many consumers have the same valuation as consumer k. Let $\pi_k(\mathbf{v}_{-k}) \equiv \pi_k(\mathbf{v}_{-k}|v_k)$ be the conditional probability of valuations other than v_k and $\mathcal{V}_{-k} \equiv \{0, v\}^{N-1}$ the corresponding set of valuations other than of consumer k.

A feasible allocation the utility

$$u_k(\mathbf{a}|v_k) = v_k x_k - t_k \tag{1.28}$$

to a consumer k with valuation v_k, and it yields the profit

$$\Pi(\mathbf{a}) = \sum_{k \in \mathcal{N}} (t_k - c x_k) - I x_0 \tag{1.29}$$

to the entrepreneur. The aggregate net surplus of allocation $\mathbf{a}$ in state $\mathbf{v}$ is therefore

$$S(\mathbf{a}|\mathbf{v}) \equiv \Pi(\mathbf{a}) + \sum_{k\in\mathcal{N}} u_k(\mathbf{a}|v_k) = \sum_{k\in\mathcal{N}} (v_k - c)x_k - Ix_0. \tag{1.30}$$

An allocation $\mathbf{a} \in \mathcal{A}$ is *Pareto efficient* in state $\mathbf{v}$ if there is no other feasible allocation $\mathbf{a}' \in \mathcal{A}$ such that $\Pi(\mathbf{a}') \geq \Pi(\mathbf{a})$, $u_k(\mathbf{a}'|v_k) \geq u_k(\mathbf{a}|v_k)$ for all $k \in \mathcal{N}$ and $\Pi(\mathbf{a}') > \Pi(\mathbf{a})$ or $u_k(\mathbf{a}'|v_k) > u_k(\mathbf{a}|v_k)$ for at least one k.

The *first-best* allocation $\mathbf{a}^*$ corresponds to the allocation that maximizes the total aggregate net surplus and is Pareto efficient in all possible states. Two types of decisions matter for first-best efficiency: the investment decision x_0 and the individual production decisions x_k. Given that the aggregate net surplus is non-negative, efficiency with respect to individual allocations requires $x_k = 1$ for all consumers with $v_k \geq c$, which yields an aggregate surplus of $\sum_{k\in\mathcal{N}}(v_k - c) \cdot \mathbb{1}_{\{v_k \geq c\}} - I$ where $\mathbb{1}_{\{\cdot\}}$ is the indicator function. Now let the set of all valuation profiles with positive aggregate net surplus be $\mathcal{V}^* \equiv \left\{\mathbf{v} \in \mathcal{V} : \sum_{k\in\mathcal{N}}(v_k - c) \cdot \mathbb{1}_{\{v_k\geq c\}} - I \geq 0\right\}$. For $\mathbf{v} \in \mathcal{V}^*$, the first-best allocation exhibits $x_0 = 1$ and $x_k = 1$ if $v_k \geq c$. For $\mathbf{v} \notin \mathcal{V}^*$, $\mathbf{a}^*$ exhibits $x_0 = x_k = t_k = 0$. The first-best allocation therefore yields an *ex-ante expected net surplus* of

$$S^* \equiv \sum_{\mathbf{v}\in\mathcal{V}^*} \sum_{k\in\mathcal{N}} \pi(\mathbf{v}) \left[(v_k - c) - I\right]. \tag{1.31}$$

Put differently, an allocation is first-best only if it leads to financing in all demand states that yield a positive surplus, regardless of how the surplus is shared between the entrepreneur and the consumers, and no financing in all other demand states. Clearly, if the entrepreneur extracts the full aggregate net surplus, that is, if $\mathbf{a}^*$ exhibits $t_k = v_k$, then the corresponding allocation is also first-best.

The entrepreneur searches for a crowdfunding mechanism to extract as much of the ex-ante expected net surplus as possible. A *mechanism* Γ is a set of rules between the entrepreneur and the N consumers that induces an arbitrary extensive-form game between them. The entrepreneur assigns an outcome to each terminal history of the game. The outcome of the mechanism is an allocation $\mathbf{a} \in \mathcal{A}$ with corresponding expected profits $\Pi(\mathbf{a})$ and expected utilities $u_k(\mathbf{a}|v_k)$. In principle, a mechanism can be any highly complex scheme or game, including simple one-stage mechanisms as well as more complicated sequential ones (of finite or infinite length). Moreover, to evaluate a given scheme, the entrepreneur must take into account the strategic behavior of consumers who participate in the scheme, that is, each consumer acts in his own interest given his expectations about the behavior of other consumers. Although the set of all possible mechanisms is vast, the *revelation principle* of Myerson (1979, 1981) allows me to focus on the well-structured sub-class of direct mechanisms where truthful revelation is an equilibrium.

A *direct mechanism* is a function $\gamma : \mathcal{V} \rightarrow \mathcal{A}$ which induces a game in which all consumers simultaneously and independently (i.e., without knowing what other consumers are writing) send a report v_k^r about their valuations to the entrepreneur. The entrepreneur collects the reported valuations $\mathbf{v}^r = (v_1^r, ..., v_N^r)$ and the funds which amount to $\sum_{k \in \mathcal{N}} t_k(\mathbf{v}^r)$ from consumers and makes an investment decision $x_0(\mathbf{v}^r)$. If the entrepreneur decides to invest, then she implements the production schedule $\mathbf{x}(\mathbf{v}^r) = (x_1(\mathbf{v}^r), ..., x_N(\mathbf{v}^r))$ as a function of the reports. A direct mechanism is thus a set of functions $\gamma(\mathbf{v}^r) = (\mathbf{x}(\mathbf{v}^r), \mathbf{t}(\mathbf{v}^r))$.

A direct mechanism is *truthful* if its induced game has a perfect Bayesian equilibrium in which each consumer optimally reports his true valuation, that is, $v_k^r = v_k$. Formally, a direct mechanism is truthful if for all $k \in \mathcal{N}$ and $v_k, v_k' \in \{0, v_L, v_H\}$ it satisfies the Bayesian *incentive compatibility* condition

$$\sum_{\mathbf{v}_{-k} \in \mathcal{V}_{-k}} \pi_k(\mathbf{v}_{-k}) \left[v_k x_k(v_k, \mathbf{v}_{-k}) - t_k(v_k, \mathbf{v}_{-k})\right] \geq \sum_{\mathbf{v}_{-k} \in \mathcal{V}_{-k}} \pi_k(\mathbf{v}_{-k}) \left[v_k x_k(v_k', \mathbf{v}_{-k}) - t_k(v_k', \mathbf{v}_{-k})\right], \tag{1.32}$$

where $x_k(v_k, \mathbf{v}_{-k})$ and $t_k(v_k, \mathbf{v}_{-k})$ denote the production decision and transfer payment, respectively, of consumer k who reports v_k, given that all other consumers report $\mathbf{v}_{-k}$. The above condition states that if a consumer's true valuation is v_k, then he is better off to report v_k rather than any other valuation v_k', given that the other consumers report truthfully.

Participation in the mechanism that the entrepreneur proposes is voluntary and hence yields at least their outside options (which I assume to be zero) to the consumers and the entrepreneur. The entrepreneur always participates because any feasible allocation yields a non-negative expected profit. By contrast, each consumer has to receive an expected utility of at least zero conditional on his own valuation. An incentive-compatible direct mechanism is *individually rational* if for all $k \in \mathcal{N}$ and $v_k \in \{0, v_L, v_H\}$

it holds that

$$\sum_{\mathbf{v}_{-k} \in \mathcal{V}_{-k}} \pi_k(\mathbf{v}_{-k}) \left[v_k x_k(v_k, \mathbf{v}_{-k}) - t_k(v_k, \mathbf{v}_{-k})\right] \geq 0. \tag{1.33}$$

Finally, a direct mechanism is *feasible* if it is incentive-compatible, individually rational for each consumer and if its induced allocations are feasible. A feasible direct mechanism yields the expected utility

$$\mathbb{E}\left[u_k(\gamma(\mathbf{v})|v_k)\right] = \sum_{\mathbf{v}_{-k} \in \mathcal{V}_{-k}} \pi_k(\mathbf{v}_{-k})[v_k x_k(v_k, \mathbf{v}_{-k}) - t_k(v_k, \mathbf{v}_{-k})] \tag{1.34}$$

to consumer k with valuation v_k and an expected profit of

$$\mathbb{E}\left[\Pi(\gamma(\mathbf{v}))\right] = \sum_{\mathbf{v} \in \mathcal{V}} \pi(\mathbf{v}) \left[\sum_{k \in \mathcal{N}} (t_k(\mathbf{v}) - c x_k(\mathbf{v})) - I x_0(\mathbf{v})\right] \tag{1.35}$$

to the entrepreneur.

1.3.2 Profit-Maximizing Crowdfunding Mechanism

The entrepreneur chooses a feasible direct mechanism $\gamma(\mathbf{v}) = (\mathbf{x}(\mathbf{v}), \mathbf{t}(\mathbf{v}))$ which maximizes expected profits subject to the incentive compatibility conditions, the individual rationality conditions and the feasibility condition. Formally, the entrepreneur solves the following problem

$$\max_{\mathbf{x}(\mathbf{v}),\mathbf{t}(\mathbf{v})} \quad \sum_{\mathbf{v} \in \mathcal{V}} \pi(\mathbf{v}) \left[\sum_{k \in \mathcal{N}} (t_k(\mathbf{v}) - c x_k(\mathbf{v})) - I x_0(\mathbf{v})\right] \tag{1.36}$$

subject to (1.32), (1.33) and

$$\sum_{k \in \mathcal{N}} (t_k(\mathbf{v}) - c x_k(\mathbf{v})) \geq I x_0(\mathbf{v}), \qquad \forall \mathbf{v} \in \mathcal{V} \tag{1.37}$$

$$x_k(\mathbf{v}) \in \{0, 1\}, \qquad \forall k \in \mathcal{N}, \forall \mathbf{v} \in \mathcal{V} \tag{1.38}$$

$$t_k(\mathbf{v}) \geq 0, \qquad \forall k \in \mathcal{N}, \forall \mathbf{v} \in \mathcal{V}. \tag{1.39}$$

Following Harris and Raviv (1981), I first simplify the problem by noting that all consumers only differ with respect to their valuations. Any two consumers who report the same valuation should also receive the same output. Although the overall output depends on the other consumers' valuations, it should only depend on the number of consumers who have either a zero or a positive valuation but not explicitly on which consumers have which valuation. Formally, this observation leads to the following symmetry property.

Lemma 1. *The problem of the entrepreneur has a symmetric solution, that is, there is a feasible direct mechanism* $\gamma^*(\mathbf{v}) = (\mathbf{x}^*(\mathbf{v}), \mathbf{t}^*(\mathbf{v}))$ *such that* $x_k^*(v_k, \mathbf{v}_{-k}) = x_1^*(\mathbf{v}')$ *and* $t_k^*(v_k, \mathbf{v}_{-k}) = t_1^*(\mathbf{v}')$ *for all* $k \in \mathcal{N}$ *and any rearrangements* $\mathbf{v}'$ *of the elements of* $\mathbf{v}$ *in which* v_k *appears in the first place.*

Proof. See Appendix A.1. □

It follows from Lemma 1 that the incentive compatibility and individual rationality constraints for consumers other than consumer 1 are redundant (even though the profit-maximizing mechanism of course still targets all consumers).

To further simplify the problem, I observe that if consumer 1 does not value the product, he also does not derive any utility from receiving the product and thus his individual rationality condition constrains him from transferring any funds to the entrepreneur.

Lemma 2. *The individual rationality and incentive compatibility constraints of a consumer with a zero valuation imply for the profit-maximizing mechanism* $\gamma^*(\mathbf{v})$*:*

(i) $t_1^*(0, \mathbf{v}_{-1}) = 0$

(ii) $x_1^*(0, \mathbf{v}_{-1}) = 0$

Proof. See Appendix A.1. □

The individual rationality and incentive compatibility constraints for consumer 1 with a zero valuation now become redundant since he neither pays a transfer, nor receives a product and hence also cannot gain anything from reporting a positive valuation. I am left with finding transfers and production schedules that satisfy the individual rationality and incentive constraints of consumer 1 with a positive valuation.

The setting at hand has the peculiar feature that consumer valuations are perfectly correlated conditional on receiving a positive valuation. It is well-established in various environments that if agents have quasi-linear preferences and their types are correlated, then the entrepreneur can implement the same allocation as if she had perfect information (e.g., Myerson, 1981; Crémer and McLean, 1985, 1988; McAfee et al., 1989). Intuitively, the entrepreneur may organize the following 'punish them all' mechanism in the current setting: all consumers report their valuations simultaneously (which is in line with the concept of direct mechanisms outlined above). If all reports coincide, then the entrepreneur implements the full-information allocation corresponding to the reported valuations. If the reports do not coincide, the entrepreneur punishes all agents by neither investing nor producing for any consumer. Clearly, it is in the interest of a consumer to report his true valuation, if he believes that all other consumers also announce their true valuation. Hence, the entrepreneur may obtain consumers' information and extract the full surplus. The following proposition formally states the corresponding full-surplus extraction result.

Proposition 1. *There exists a feasible direct mechanism which implements full-surplus extraction for the entrepreneur as an equilibrium.*

Proof. See Appendix A.1. □

While the insight that the entrepreneur may exploit the correlation in consumers' positive valuations to extract the full surplus is economically important, it is hard to grasp in practice.

In particular, even though a full-surplus extraction equilibrium exists, there are many more equilibria in the corresponding mechanism (with the number of equilibria in fact increasing as the number of consumers increase). Specifically, the full-surplus extraction equilibrium hinges on consumers' beliefs that (other) high-valuation consumers truthfully report a high valuation.[7] However, there are several other equilibria in which a high-valuation consumer believes that at least some of the consumers do not truthfully report. In case some consumers misreport, the entrepreneur does neither produce nor make any profits in the 'punish them all' mechanism. There also exists an equilibrium in which a high-valuation consumer believes that all other consumers misreport their true valuation. In this equilibrium, all consumers with valuation v_H falsely report the valuation v_L. This collective deception in fact yields higher expected utility for consumers with high valuations. In particular, if all consumers with a valuation v_H report v_L, then each of them receives $v_H - v_L$ in demand state (n_H, v_H),

[7] Several other crucial assumptions for the full-surplus extraction results have been identified in the literature, for example, risk neutrality (Robert, 1991), absence of collusion among agents (Laffont and Martimort, 2000), or absence of competition among sellers (Peters, 2001). Although the current setting also features these simplifications, further extensions along these lines go beyond the scope of this paper.

whereas they get zero expected utility in this state under full rent extraction of the entrepreneur. The entrepreneur not only surrenders part of the profits of state (n_H, v_H) in this deception equilibrium but also loses the profits of the (n_L, v_H) equilibrium. The construction of the truth-telling equilibrium of the direct mechanism hence does not exclude the possibility of other equilibria in which the consumers are not telling the truth and the profit-maximizing outcome is not realized.

Therefore, I follow the robust implementation approach (e.g., Bergemann and Morris, 2009, 2011) and refine the search for a profit-maximizing mechanism to the set of mechanisms with the property that, for any beliefs (and higher-order beliefs) that the consumers may have, every equilibrium features truthful reporting. Instead of supposing that other consumers report truthfully, robust implementation guarantees that truthful behavior results. A feasible direct mechanism is hence *belief-robust* if consumers report truthfully in every equilibrium that the mechanism can implement. In particular, a direct mechanism is belief-robust if for all $k \in \mathcal{N}$, $v_k, v'_k \in \{0, v_L, v_H\}$, and all valuations reported by other consumers $\mathbf{v}^r_{-k} \in \mathcal{V}_{-k}$ it satisfies the incentive compatibility condition

$$\sum_{\mathbf{v}^r_{-k} \in \mathcal{V}_{-k}} \pi_k(\mathbf{v}^r_{-k}) \left[v_k x_k(v_k, \mathbf{v}^r_{-k}) - t_k(v_k, \mathbf{v}^r_{-k}) \right] \geq \sum_{\mathbf{v}^r_{-k} \in \mathcal{V}_{-k}} \pi_k(\mathbf{v}^r_{-k}) \left[v_k x_k(v'_k, \mathbf{v}^r_{-k}) - t_k(v'_k, \mathbf{v}^r_{-k}) \right]. \tag{1.40}$$

This additional requirement leads to the following lemma.

Lemma 3. *The individual rationality and incentive compatibility constraints of a consumer with a positive valuation imply for the belief-robust profit-maximizing direct mechanism:*

(i) $t^*_1(v_L, \mathbf{v}^r_{-1}) = v_L x^*_1(v_L, \mathbf{v}^r_{-1})$

(ii) $t^*_1(v_H, \mathbf{v}^r_{-1}) = v_H x^*_1(v_H, \mathbf{v}^r_{-1}) - (v_H - v_L) x^*_1(v_L, \mathbf{v}^r_{-1})$

(iii) $x^*_1(v_H, \mathbf{v}^r_{-1}) \geq x^*_1(v_L, \mathbf{v}^r_{-1})$

for all valuations reported by other consumers $\mathbf{v}^r_{-1}$.

Proof. See Appendix A.1. □

The first statement in Lemma 3 establishes that if the entrepreneur produces for a consumer who reports a low valuation, then she may charge the transfer payment v_L.

The second part states that the entrepreneur may extract the full information rent from consumers with valuation v_L, but she may not do so for consumers with valuation v_H (who may prefer to report v_L) at the same time. If the entrepreneur does not produce for consumers who send a low valuation, then she may produce for consumers who report a high valuation and charge them v_H. The third part of the lemma corresponds to the requirement that if the entrepreneur produces for consumers who send v_L, then she also has to produce for consumers who report v_H.

Using the above lemmas, I now turn to the question whether the entrepreneur may extract the full surplus of the crowdfunding game under a belief-robust mechanism. The next proposition establishes a condition under which the entrepreneur is able to implement first-best allocations under the belief-robust mechanism but at the same time has to grant consumers an information rent.

Proposition 2. *If the demand states satisfy*

$$(1-\pi_v)\left[n_H(v_L-c)-I\right] \geq \pi_v n_H\left(v_H-v_L\right), \tag{1.41}$$

then the belief-robust profit-maximizing crowdfunding mechanism implements first-best allocations where consumers with valuation v_L do not receive any surplus and each consumer with valuation v_H receives the information rent $v_H - v_L$ in state (n_H, v_H) and no information rent in the other states.

Otherwise, the belief-robust profit-maximizing crowdfunding mechanism implements allocations where the entrepreneur only produces for consumers with valuation v_H who do not receive any information rents. Moreover, the belief-robust profit-maximizing crowdfunding mechanism is in this case only first-best if states with v_H are the only feasible states.

The proposition states that the entrepreneur only finds it optimal to implement first-best allocations under the belief-robust mechanism if the expected profits in state (n_H, v_L) exceed the expected surplus which the entrepreneur cedes to consumers in state (n_H, v_H) where consumers with a high valuation receive the information rent $v_H - v_L$. The first-best funding outcome may therefore only be achieved under particular circumstances for the belief-robust profit-maximizing mechanism. Consumers with the high valuation require the prospect of receiving the low price in some demand states to always truthfully reveal their valuation. Alternatively, if this information rent is too large, the entrepreneur only produces for consumers with high valuations and consumers with low valuations never receive a product.

1.4 Discussion

This section interprets the insights of the previous sections and discusses potential extensions and robustness of the results. First, both the intuitive crowdfunding campaign and the belief-robust profit-maximizing mechanism rely on the entrepreneur's commitment to a pricing strategy and to deliver the product after a successful campaign. I hence discuss the potential implications of the lack of such commitments. Second, I sketch how crowdfunding platforms work in practice and how they might implement the state-contingent mechanism. Lastly, I elaborate on the potential replication of the belief-robust profit-maximizing crowdfunding mechanism through security contracts.

1.4.1 Lack of Commitment

Following Harris and Raviv (1981) and Strausz (2017), I assume that the entrepreneur can commit to a price schedule in advance. In the absence of such price commitment, crowdfunding consumers might be confronted with two types of time-consistency problems of the entrepreneur: one with respect to the prices they pay and one related to the prices potential future consumers pay.

The entrepreneur might have an incentive to change the price that she charges consumers upon observing their valuations. In particular, if consumers report high valuations, the entrepreneur might prefer to charge them a high price to reap the full consumer surplus. The entrepreneur's lack of commitment requires that the initially proposed price schedule maximizes her profits even after observing the demand reported by consumers. Intuitively, the entrepreneur's inability to commit reduces her profits since consumers anticipate the entrepreneur's deviation from the promised pricing scheme. High-valuation consumers might hence be more reluctant to communicate their true valuation due to the fear of the entrepreneur reaping their information rent ex-post. In the extreme case where the entrepreneur always charges consumers the high price whenever they report high valuations, consumers with high valuation refrain from sending truthful reports altogether as it is not incentive compatible to do so. Acknowledging these ramifications of her lack of commitment, the entrepreneur has an incentive to avoid this type of time-consistency problem.

In addition, the entrepreneur faces a potential time-consistency problem analogous to the one studied in the durable goods literature (e.g., Coase, 1972; Stokey, 1981; Bulow, 1982; Gul et al., 1986). Namely, after having observed the reported valuations of consumers, the entrepreneur might have an incentive to adjust the price that she charges consumers on the market after crowdfunding, that is, the secondary market. Suppose that, in addition to the crowdfunding consumers of the current framework, there are secondary-market consumers who do not have access to the crowdfunding mechanism (e.g., due to inattention). If the valuations on the secondary market are perfectly correlated with those of the crowdfunding users, then the entrepreneur charges the same price in both markets and no issues arise. However, if high valuations in the crowdfunding market are consistent with low valuations in the secondary market, then the entrepreneur has an incentive to charge the low price in the secondary market. Absent any discounting, high-valuation consumers might be willing to wait for the secondary market or prefer to report low valuations in this case. This type of time-consistency problem might thus hamper the screening benefits of crowdfunding.

Moreover, upon observing consumers' valuations, the entrepreneur might decide to cancel a successful crowdfunding campaign and seek external financing with the newly acquired demand information. Given that the entrepreneur has elicited both the market size and consumers' reservation price, she might want to raise the investment costs from a competitive credit market. However, as the entrepreneur does not maintain her promise to deliver the product, consumers do not receive any products through crowdfunding and are left with the option to buy the product at a possibly higher price on the secondary market. Again, anticipating the entrepreneur's lack of commitment to deliver the product hampers consumers' incentives to truthfully report their valuations.

1.4.2 Crowdfunding Mechanisms in Practice

The theoretical crowdfunding mechanisms discussed above come in two different variants (depending on parameter constellations): the entrepreneur either specifies a fixed price for her product or a state-contingent price schedule that depends on the the number of pledgers.

In practice, a crowdfunding platform intermediates between the entrepreneur and her crowdfunding consumers. On the one hand, crowdfunding platforms require consumers to pay their bids in advance rather than committing to buy the product at the pricing rule specified in the campaign (cf. the intuitive campaign of Section 1.2) or sending their valuations (cf. the direct mechanism of Section 1.3). Entrepreneurs, on the other hand, are only allowed to set fixed prices at campaign launch, change the price of a reward as long as it has not attracted any pledgers yet, or add a new reward throughout the life of a campaign. Platforms collect consumers' funds throughout the campaign and transfer them to the entrepreneur only if the campaign reaches the funding goal after it expired. A crowdfunding platform hence effectively serves as a commitment device for the entrepreneur's strategy based on fixed prices.

A direct replication of the state-contingent pricing rule where the entrepreneur specifies that the price for the reward decreases as the number of pledgers increases can hence not be found in practice. However, while crowdfunding platforms feature prespecified menus of rewards at fixed prices, these prices usually serve as a *minimum* pledge amount, that is, consumers may voluntarily pledge funds in excess of the prices specified in the campaign. Consumers may also change pledge amounts by either increasing the money spent for a certain reward or switching to a different reward throughout the whole campaign life. Although pledge dynamics during a campaign are outside of my model, these notions still allow me to sketch potential implementations of the state-contingent mechanism.[8]

Initially, the entrepreneur may launch the campaign with low prices. Upon observing that only few consumers pledged funds at the low price and that the project is not viable at this level of aggregate demand, the entrepreneur may contact consumers and ask them for higher contributions, effectively proposing consumers to pay the high price for the product to ensure the project's viability. Alternatively, entrepreneurs may add a new reward where they offer essentially the same product but at a higher price. Consumers may then update their pledges to the new reward category and pay a higher price. Crowdfunding campaigns typically do not feature exactly the same reward at different prices. Rather, entrepreneurs offer slightly differentiated products at different prices. While product differentiation is outside of my model, the overall idea is that high-valuation consumers may select the high-price reward after they observed that there are only few pledgers.

Naturally, if consumers are not willing to pay higher prices by either sending more funds or upgrading to a new reward category, then the crowdfunding campaign is deemed a failure. Both strategies also give rise to a free-riding problem where an individual consumer wants the other consumers to pay higher prices but keeps his own contribution low. However, my analysis abstains from free-riding by focusing on

[8] I refer to Cong and Xiao (2018) for a study of the dynamics of consumers' pledging behavior within a given campaign.

mechanisms where truthful behavior is (weakly) optimal for all consumers.

1.4.3 Replication through Security Contracts

While reward-based crowdfunding allows the entrepreneur to elicit consumer preferences, entrepreneurs may in principle also directly offer securities to consumers to finance investment costs, which is typically called *crowd-investing* (e.g., Li, 2016; Brown and Davies, 2018; Terovitis, 2019). An explicit modeling of security design is outside of my framework, but I may still interpret reward-based crowdfunding as the sale of financial contracts between the entrepreneur and consumers.

It may be tempting to relate reward-based crowdfunding to initial public offerings (IPOs). In fact, one strand of the IPO literature follows the notion that outside investors may have superior information about the firm compared to insiders, for example, soft information on management quality, the ability to outperform competitors, or forecasts about future developments in the company, industry, or economy (e.g., Rock, 1986; Benveniste and Spindt, 1989; Sherman, 2005). In this literature, IPO selling mechanisms are designed to maximize IPO proceeds and elicit information from privately informed investors. The key tension in IPO selling mechanisms arises between selling securities at fixed prices, which allows for underpricing to attract informed investors, and auctioning off shares, which maximizes proceeds but deters information production.

In the context of my model, three crucial differences to said IPO literature emerge. First, the valuation problem underlying an IPO is fundamentally more complex than the valuation of a product. For instance, investors not only care about demand at the crowdfunding stage but also about demand on the market after investment. Consumers in the crowdfunding setting just want the product (or not) but do not care about aggregate demand as long at it is sufficient for the entrepreneur to invest.

Second, consumers who constitute potential outside investors are only partially informed about the value of the firm through their private knowledge of their own valuation. However, consumers do not possess information about the valuations of other consumers, that is, they do not know how many consumers value the product positively. In principle, the entrepreneur may auction off shares in the firm directly to consumers. However, this auction can at best only aggregate consumers' information about product valuations together with their beliefs about the market size. Due to the lack of information about the market size, this funding mechanism cannot implement first-best financing outcomes under all circumstances. Instead, by committing to a price in the crowdfunding campaign ex-ante, the entrepreneur (and consumers alike) may learn about the market size before they make an investment decision.

Third, IPOs involve the sale of a fixed quantity of claims on the value of the firm. Suppose those claims directly map into claims on the future product. In the context of crowdfunding, the entrepreneur does not want to commit to a fixed quantity of claims on the future product. Suppose the entrepreneur decides to auction off a fixed quantity of claims on the future product. Moreover, suppose that the supply of claims is below the potential market size and thus creates scarcity. The scarcity of claims is crucial to incentivize consumers' truthful revelation in the auction. However, upon observing consumers' valuation through an auction, the entrepreneur has an incentive to sell more quantities of the product ex-post. But this time inconsistency leads to a failure of the auction to begin with.

Furthermore, as the entrepreneur sells claims that promise a fixed repayment in the future (in the form of the prospective product), reward-based crowdfunding shares a closer resemblance to debt contracts rather than equity. Intuitively, the state-contingent pricing rule exhibits cash flows that may be interpreted as a combination of debt and credit lines that the entrepreneur may draw on in some demand states. More specifically, the entrepreneur may borrow v_L from each consumer and offer them a fixed repayment of v_L (regardless of whether she develops the product or not). In addition, the entrepreneur asks consumers for a credit line that allows her to withdraw an additional $v_H - v_L$ in demand state (n_L, v_H) but nothing in demand state (n_H, v_L). These payments yield the same expected profits and utilities as the profit-maximizing crowdfunding mechanism but may be regarded as traditional financing tools.[9]

1.5 Conclusion

Reward-based crowdfunding involves the sale of claims on the future product to finance product development costs. By committing to a price of the product in the funding stage, entrepreneurs may observe the number of consumers who are interested in buying the product at that particular price. Entrepreneurs thereby learn about product demand and may improve their screening for viable investments vis-à-vis financing through uninformed outside investors.

[9] The notion that the optimal security mix under asymmetric information is a combination of credit lines, debt and equity follows DeMarzo and Sannikov (2006) and DeMarzo and Fishman (2007).

I consider a setting where consumers have private information about their individual valuations and demand uncertainty has two facets: the entrepreneur does not know the number of consumers who value her product positively (the market size) nor does she observe the common private positive valuation of consumers (the reservation price). Entrepreneurs may choose fixed prices which preclude financing of some demand states that are nonetheless profitable. Alternatively, entrepreneurs may commit to price schedules that depend on the number of contributors to the crowdfunding campaign. This pricing scheme specifies that consumers with low reservation prices always pay their reservation price, while consumers with high reservation prices pay their true reservation price as long as there are few contributors and the low price when there are many pledgers. Entrepreneurs may hence exploit the uncertainty about the market size to incentivize consumers' participation. This state-contingent pricing scheme ensures that all viable projects get financing if different combinations of market size and consumer reservation prices yield positive profits.

Using mechanism design theory, I characterize the profit-maximizing crowdfunding mechanism in the setting where the entrepreneur faces uncertainty with respect to the distribution from which consumers' private valuations are drawn. The correlation in consumers' valuations (conditional on receiving a positive valuation) in principle allows the entrepreneur to extract the full surplus. However, the corresponding mechanism is sensitive to consumers' beliefs about other consumers' behavior and features only one equilibrium with full-surplus extraction for the entrepreneur. The belief-robust profit-maximizing mechanism ensures truthful behavior but in general does not allow the entrepreneur to extract the full consumer surplus since she either has to grant consumers with high valuations an information rent or does not produce for low-valuation consumers. Moreover, the belief-robust profit-maximizing mechanism does only lead to first-best financing outcomes under certain parameter constellations with respect to consumers' information rent.

While existing features of crowdfunding platforms may in principle allow for an indirect implementation of the state-contingent pricing rule, there are a number of potential impediments and interactions that are outside of my framework. For instance, I do not consider the simultaneous presence of different positive consumer valuations which would give rise to different forms of price discrimination or product differentiation. I also do not model moral hazard or private cost information on the entrepreneur's side. Hidden actions and asymmetric information on both sides of the crowdfunding game might impose further limits on the potential of crowdfunding to finance ventures, but they might also open up avenues for other potentially complementary financing tools (e.g., venture capital).

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2 Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets

Joint work with Nikolaus Hautsch and Stefan Voigt

Distributed ledger technologies replace trusted clearing counterparties and security depositories with time-consuming consensus protocols to record the transfer of ownership. This settlement latency exposes cross-market arbitrageurs to price risk. We theoretically derive arbitrage bounds that increase with expected latency, latency uncertainty, volatility, and risk aversion. Using Bitcoin order book and network data, we estimate arbitrage bounds of, on average, 121 basis points, explaining 91% of the observed cross-market price differences. Consistent with our theory, periods of high latency-implied price risk exhibit large price differences, while asset flows chase arbitrage opportunities. Blockchain-based settlement thus introduces a non-trivial friction that impedes arbitrage activity.

2.1 Introduction

Traditional security markets are organized around trusted intermediaries that enable seemingly frictionless trading on and across different markets. For instance, central counterparty clearing covers counterparty risks between transacting parties during the time window from the execution of a trade to the legal transfer of ownership through security depositories. This form of clearing allows for a temporal separation of the settlement process, which typically takes two to three business days (e.g., SEC, 2017), and the process of trading on still unsettled positions. In contrast, distributed ledger technologies promise secure, fast, and cheap settlement without the need of such designated intermediaries. Instead of relying on trusted third parties, decentralized validators interact with each other to establish consensus about transaction histories and the transfer of ownership (e.g., Biais et al., 2019). Consensus protocols specify how validators may reach agreement and how fast this agreement may be accomplished, which is typically in the order of a few minutes. Decentralized systems thus considerably speed up the process of settlement compared to markets with central clearing and settlement. However, at the same time distributed ledger technologies slow down individual market participants who cannot dispose of positions before validators record the transfer of ownership in the ledger.

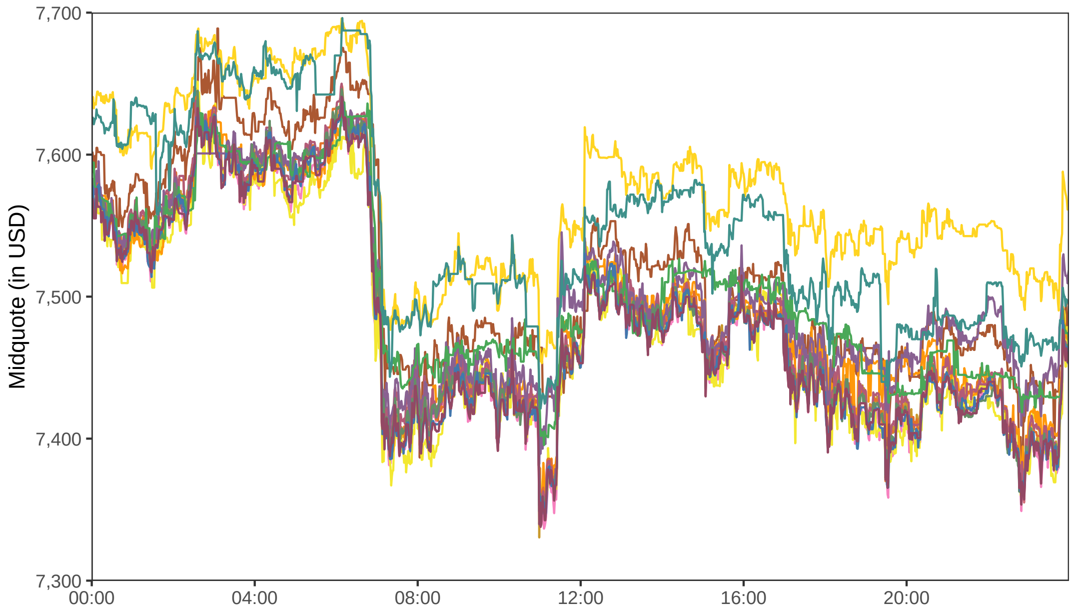
Replacing trusted intermediaries with time-consuming consensus protocols thus exposes cross-market traders to a new type of latency that restricts them in their flexibility to trade (and thus to react to changing market conditions) sufficiently fast. We refer to this period as *settlement latency*, which does not only determine the speed of clearing but—unlike in traditional markets—also affects the speed of trading. This latency is an inherent feature of distributed ledger systems and is several magnitudes larger than execution latencies in traditional markets (e.g., Chiu and Koeppl, 2019; Easley et al., 2019). In that sense, distributed ledger technologies exhibit a direct link between the process of trading and the process of settlement.

In this paper, we show that the latency caused by decentralized settlement imposes limits to (statistical) arbitrage since arbitrageurs cannot immediately exploit cross-market price differences. This friction is particularly relevant whenever there is no possibility to bypass settlement latency without any risks or costs, that is, whenever (margin-based) short-selling is costly and cross-exchange inventory holdings are risky. In these scenarios, limits to arbitrage arise and may explain severe and persistent violations of the law of one price.

As an illustration, Figure 2.1 provides compelling evidence for such violations of the law of one price. The plot shows the midquotes of different exchanges that feature trading of Bitcoin, a cryptocurrency that is settled on a distributed ledger, against US Dollar for a representative day in 2018. The average daily price difference across all exchange pairs through our sample is around 33 bp and thus economically (highly) significant. As Choi et al. (2018) or Makarov and Schoar (2020) also report, these price differences persist, are not traded away, and (as we show in this paper) cannot be reconciled solely with transaction costs.

We document that arbitrage bounds due to settlement latency can explain a major part of the magnitude and time variation of these price differences. Our analy-

Figure 2.1: Bitcoin-US Dollar Midquotes on May 25, 2018



Notes: This figure shows the midquotes of one Bitcoin in US Dollar on May 25, 2018, for 16 different exchanges. We gather high-frequency order book information by accessing the public application programming interfaces (APIs) of each exchange every minute. We calculate midquotes as the average of the best bids and best asks.

sis builds on a general theoretical framework that shows how settlement latency in a volatile market translates into bounds below which price differences may vary without being arbitraged away by risk-averse arbitrageurs. We model the trading decision of an arbitrageur who monitors prices on different markets but faces settlement latency, which limits her possibility to exploit concurrent price differences between two markets. In fact, whenever she buys on one market (at the current price), she has to wait until the transfer of the asset is validated before she can sell on the other market. The latency underlying this transfer thus exposes arbitrageurs to the risk of adverse price movements. Consequently, risk-averse arbitrageurs only exploit (concurrent) price differences if these price differences are sufficiently large to compensate for the price risk during the settlement period. This reluctance to trade gives rise to bounds above which a risk-averse arbitrageur exploits violations of the law of one price. Price differences below these bounds, however, may persist, as they are consistent with the risk-return trade-off of a rational arbitrageur.

In our theoretical setting we thus focus on a scenario in which any intermediation services, which allow to bypass settlement latency, are either not available or are too costly. In fact, in a distributed ledger system such financial intermediation either does not exist at all (if the idea of decentralization without designated intermediaries is fully internalized) or can implicitly only be provided by the trading platforms themselves. Since such intermediation confronts the exchanges with counterparty and credit risk, such services are either not available, very limited, or costly. Hence, we consider situations, where inventory holdings on an exchange are too expensive, too risky, or exhausted and short-selling is prohibitively expensive or not possible. In that sense, our model allows us to quantify the economic frictions (in terms of arbitrage bounds) that arise if a central clearing counterparty—which essentially enables continuous trading through immediate clearing—is replaced by a time-consuming decentralized consensus mechanism. Our results are independent of the specific underlying technology and sufficiently general to be applicable to other types of latencies on financial markets (for instance, execution latencies).

We provide closed-form expressions for the arbitrage bounds under fairly general assumptions and show that they increase with (i) the arbitrageurs risk aversion, (ii) the volatility on the sell-side market, (iii) the expected settlement latency, and (iv) the variance of the settlement latency. Our characterization of the arbitrage bounds also accounts for transaction costs and settlement fees that traders may choose to give validators an incentive to enable a fast validation.

We use minute-level data from order books of 16 exchanges that feature trading Bitcoin against US Dollar between January 2018 and October 2019. The order books allow us to detect potential arbitrage opportunities between each exchange pair, taking transaction costs such as trading fees and market impact into account. Furthermore, we gather comprehensive information about the Bitcoin network, including the time it takes for every transaction from entering the Bitcoin network until its inclusion in the blockchain, that is, its settlement. Using this information, the estimation of arbitrage bounds rests on three ingredients. First, we construct estimates of exchange-specific spot volatilities based on minute-level best bid quotes. Second, we parametrize the latency distribution as a conditional gamma distribution depending on network and transaction-specific characteristics that affect the settlement latency. Third, in line with the existing literature, we choose an isoelastic utility function with exogenously given coefficient of relative risk aversion.

The average estimated arbitrage bound for a relative risk aversion of 2 amounts to 121 bp. This magnitude constitutes an economically highly significant friction and may explain severe distortions of the law of one price. We find that 84% of all observed concurrent price differences based on best bids and asks across markets fall within these bounds. Adjusting additionally for transaction costs, the bounds contain even up to 91% of the observed price differences. Equivalently, we show that the average implied relative risk aversion necessary to explain all observed concurrent cross-exchange price differences amounts to 17. This estimate is high compared to existing estimates of coefficients of relative risk aversion in the asset pricing literature (e.g., Hansen and Singleton, 1982; Chetty, 2006) and suggests the existence of additional market frictions as settlement latencies and transaction costs cannot fully explain all (apparent) arbitrage opportunities.

We show that the derived arbitrage bounds can explain a substantial portion of both the magnitudes of observed cross-market price differences and their variation over time. This explanatory power persists even if we control for additional market frictions such as market illiquidity, the absence of margin trading, and risky inventory holdings (e.g., Pontiff, 1996; Lamont and Thaler, 2003a,b; Roll et al., 2007; De Jong et al., 2009). In particular, we find that large cross-exchange price differences coincide with episodes of high limits to arbitrage, which are in turn driven by high volatilities and long settlement latencies.

Finally, we show that the market perceives arbitrage opportunities and limits thereof. In fact, we illustrate that variations in price differences between exchanges trigger variations in cross-exchange asset flows. To perform this analysis, we collect wallets that are under the control of the exchanges in our sample and compile a unique and novel data set of 3.9 million cross-exchange transactions with an average daily volume of 72 million US Dollar. Using the derived limits to arbitrage as instruments for cross-exchange price differences, we tackle the inherent endogeneity arising from the simultaneity between price differences and cross-exchange asset flows. We find that asset flows into an exchange significantly respond to variations in concurrent price differences, particularly those explained by variations in limits to arbitrage, while we also control for latency-induced price risk and exchange-specific characteristics. We thus contribute to the literature on limits to arbitrage (e.g., De Long et al., 1990; Shleifer and Vishny, 1997; Gromb and Vayanos, 2010) by highlighting a friction that arises in decentralized markets and which impedes arbitrageurs' ability to exploit mispricing.

Our results also contribute to a better understanding of the economic implications of distributed ledger systems for trading on financial markets. In fact, the promise of fast and low-cost transaction settlement leads central banks and marketplaces to actively explore potential applications of such systems for transaction settlement (e.g., BIS, 2017; NASDAQ, 2017; ECB and BoJ, 2018; SIX, 2018). While existing papers typically focus on the costs associated with the decentralized settlement process and potential welfare gains (e.g., Abadi and Brunnermeier, 2018; Chiu and Koeppl, 2019), we consider the implications of blockchain-based settlement for cross-market trading. Our emphasis lies on the economic frictions that originate from the time-consuming effort necessary to establish trust in blockchain-based markets. The absence of trusted intermediaries does not only expose arbitrageurs to price risk but also exposes exchanges to counterparty risk.

Most exchanges, therefore, require *several* confirmations to regard an incoming transaction as valid, rather than just a single one. These additional confirmation requirements reflect the inherent fear of fraudulent transactions from so-called double spending attacks, where an attacker tries to spend his funds twice in different transactions. Requiring multiple confirmations by the network decreases the success probability of such an attack, as the reversal of a transaction becomes computationally more involved the more advanced the overall transaction history is. Some exchanges in our sample require up to 5 additional confirmations, which, apart from increasing security, also considerably scales up settlement latency. Hence, with decentralized settlement, exchanges only achieve trust through sufficiently high security requirements, which make it prohibitively hard to manipulate the system. This security, however, comes at the cost of increased (computational) complexity, which in turn takes time. To quantify the costs of these additional security requirements, we compare the arbitrage bounds of a (hypothetical) scenario, where all exchanges require just one confirmation, to a (hypothetical) scenario where all exchanges require ten confirmations. We find that the estimated arbitrage bounds increase by on average 7 bp per additional confirmation.

These costs are economically significant and explain recent efforts of blockchain-based marketplaces to circumvent settlement latencies via the introduction of fast private inter-exchange settlement networks.[1] However, any attempt to bypass the settlement latency in decentralized markets by reintroducing the functions of third-party clearing effectively undermines the fundamental principle of decentralized settlement which deliberately abstains from all designated intermediaries. In practice, marketplaces may adopt the role of clearing houses and take over counterparty risk dur-

[1]For instance, since October 2018, the company *Blockstream* has been running a private side-chain to the main Bitcoin blockchain which connects several exchanges and allows for transfer of assets between exchanges in less than 2 minutes.

ing the settlement period. The internal netting procedures of exchanges, however, only work with high collateral requirements. It is thus impossible to bypass the waiting time necessary to establish sufficient security and trust in a decentralized system without any other costs or frictions. Settlement and validation by a distributed ledger system without any intermediaries is hence fundamentally not compatible with fast trading. Our paper provides theoretical and empirical guidance for the quantification of the economic frictions that arise whenever trusted clearing counterparties—which may be regarded as a different type of friction—are removed.

2.2 Settlement Latency and Limits to Arbitrage

2.2.1 Arbitrage Returns under Settlement Latency

We consider an economy containing a single asset that is traded on two different markets b and s. The trading activity on these markets is exogenously given and we assume that agents can continuously monitor the quotes of the asset across all markets. We assume that market $i \in \{b, s\}$ continuously provides marginal buy quotes (asks) A_t^i and sell quotes (bids) B_t^i (with $B_t^i \leq A_t^i$) for one marginal unit of the asset at time t. We address the possibility to trade more than one marginal unit of the asset and the consideration of transaction costs in the next section and show that these generalizations do not affect our main insights.

Our sole agent is an arbitrageur who aims to exploit observed price differences across markets. The arbitrageur continuously monitors the quotes on markets b and s and considers the following strategy: if buying on one market and selling on the other market implies a profit, she intends to buy a marginal unit of the asset on the market with the lower buy quote, transfer the asset to the market with a higher sell quote and sell it as soon as the transfer is settled.

We assume that (margin-based) short-selling is too costly to render a short-based strategy profitable or, alternatively, that margin constraints, which would allow for short sales, bind. Similarly, we assume that inventory holdings on any of the markets are too risky or are exhausted. In that sense, we consider a scenario where, upon observing the quotes, any cross-market price differences have already been absorbed up to the point where the arbitrageur is forced to physically transfer the asset between markets.

Without loss of generality, we focus on a scenario where the arbitrageur buys on market b and sells on market s. The converse case of selling on market b and buying on market s can be handled analogously. Hence, in case of frictionless trading and no latency in settlement, the arbitrageur exploits observed price differences if

$$B_t^s > A_t^b, \tag{2.1}$$

as she can buy the asset on market b at A_t^b, instantaneously transfer the asset to market s and sell it again at price B_t^s.

An instantaneous transfer is not possible, however, whenever the settlement of the transaction is time-consuming. Such a (possibly random) latency constitutes a fundamental element of distributed ledger systems that do not rely on central clearing entities. It should not be confused, however, with latency in *order execution* as heavily discussed in the context of high-frequency trading (e.g., Hasbrouck and Saar, 2013; Foucault et al., 2017). Such latencies are in the order of milliseconds and thus of several magnitudes smaller than settlement latencies. Therefore, without loss of generality, we refrain from latency in order execution and assume that markets process orders instantaneously.

Let latency τ denote the random waiting time until a transfer of the asset between markets is settled. If the buy transaction on market b takes place at time t and the transfer of the asset to market s is settled at $t+\tau$, the arbitrageur faces the sell quote $B_{t+\tau}^s$. The profit of the arbitrageur's trading decision is thus at risk if the probability of losing money is non-zero, that is, if

$$\mathbb{P}\left(B_{t+\tau}^s < A_t^b\right) > 0. \tag{2.2}$$

In this case, a risk-averse arbitrageur faces limits to (statistical) arbitrage whenever the associated risk exceeds the expected return (see, e.g., Bondarenko, 2003). To formalize the trading decision of the arbitrageur, denote the log quotes by $a_t^b := \log\left(A_t^b\right)$ and $b_t^s := \log\left(B_t^s\right)$, respectively, to cast the payoff in log returns. The log return resulting from buying on market b at time t and selling on market s at time $t+\tau$ is then given by

$$r_{(t:t+\tau)}^{b,s} := b_{t+\tau}^s - a_t^b = \underbrace{\delta_t^{b,s}}_{\substack{\text{instantaneous}\\ \text{return}}} + \underbrace{b_{t+\tau}^s - b_t^s}_{\substack{\text{exposure to}\\ \text{price risk}}}, \tag{2.3}$$

where $\delta_t^{b,s} := b_t^s - a_t^b$ defines the return the arbitrageur would earn under instantaneous settlement, that is, in the absence of any latency. The second part of the decomposition captures the risk of adverse price movements on the sell-side market. As the instantaneous return $\delta_t^{b,s}$ is observable and thus known in t, the arbitrageur only faces uncertainty about the evolution of prices on the sell-side market. The price process on the sell-side market is given as follows.

Assumption 1. *For a given latency τ, we model the log price change on the sell-side $b_{t+\tau}^s - b_t^s$ as a Brownian motion with drift μ_t^s such that*

$$r_{(t:t+\tau)}^{b,s} = \delta_t^{b,s} + \tau\mu_t^s + \int_t^{t+\tau} \sigma_t^s dW_k^s, \tag{2.4}$$

where σ_t^s denotes the spot volatility of the bid quote process on market s, and W_k^s denotes a Wiener process. We assume that σ_t^s is constant over the interval $[t, t+\tau]$ and rule out any jumps.[2]

The dynamics of the sell price thus expose the arbitrageur to uncertainty about her profits. The uncertainty is triggered by the spot volatility σ_t^s and the latency τ. We require only weak assumptions regarding the stochastic nature of the latency.

Assumption 2. *The stochastic latency $\tau \in \mathbb{R}_+$ is a random variable equipped with a conditional probability distribution $\pi_t(\tau) := \pi(\tau|\mathcal{I}_t)$, where $\mathcal{I}_t$ denotes the set of available information at time t. We assume that the moment-generating function of $\pi_t(\tau)$, defined as $m_\tau(u) := \mathbb{E}_t(e^{u\tau})$ for $u \in \mathbb{R}$, is finite on an interval around zero.*

Assumptions 1 and 2 allow us to fully characterize the return distribution $\pi_t\left(r_{(t:t+\tau)}^{b,s}\right)$ through the interval of random length from t to $t+\tau$ for a wide range of latency distributions.

Lemma 4. *Under Assumptions 1 and 2, the returns follow a normal variance-mean mixture with probability distribution*

$$\pi_t\left(r_{(t:t+\tau)}^{b,s}\right) = \int_{\mathbb{R}_+} \pi_t\left(r_{(t:t+\tau)}^{b,s}|\tau\right)\pi_t(\tau)\,d\tau, \tag{2.5}$$

[2] Time-varying and stochastic volatility can be incorporated by means of a change of the time-scale of the underlying Brownian motion. We provide the corresponding derivations in Appendix B.2. However, both the time-variability of σ_t^s and the presence of jumps would further increase the price risk the arbitrageur is facing. In that sense, the bounds derived in this paper are conservative.

and corresponding characteristic function[3]

$$\varphi_{r^{b,s}_{(t:t+\tau)}}(u) = e^{iu\delta^{b,s}_t} m_\tau \left(iu\mu^s_t - \frac{1}{2}u^2(\sigma^s_t)^2 \right). \tag{2.6}$$

Proof. See Appendix B.1. □

For any valid distribution $\pi_t(\tau)$, Lemma 4 characterizes the impact of stochastic latency on the return distribution. In Appendix B.3, we illustrate the special case where $\pi_t(\tau)$ follows an exponential distribution and show that the resulting return distribution follows an asymmetric Laplace distribution.

2.2.2 Arbitrage Bounds for Risk-Averse Arbitrageurs

To quantify the arbitrageur's assessment of risk, we have to equip her with a corresponding utility function.

Assumption 3. *The arbitrageur has a utility function $U_\gamma(r)$ with risk aversion parameter γ, where r are the log returns implied by her trading decision. Furthermore, we assume $U'_\gamma(r) > 0$ and $U''_\gamma(r) < 0$.*

The arbitrageur maximizes the expected utility $\mathbb{E}_t\left(U_\gamma(r)\right)$, which we express in terms of the certainty equivalent (CE). We derive the CE of exploiting concurrent cross-market price differences in the following theorem.

Theorem 1. *Under Assumptions 1–3, the certainty equivalent (CE) resulting from the arbitrage trade is given by*

$$\begin{aligned} CE =& \delta^{b,s}_t + \mathbb{E}_t(\tau)\mu^s_t \\ &+ \sum_{k=2}^{\infty} \frac{U^{(k)}_\gamma\left(\delta^{b,s}_t + \mathbb{E}_t(\tau)\mu^s_t\right)}{k!U'_\gamma\left(\delta^{b,s}_t + \mathbb{E}_t(\tau)\mu^s_t\right)} \mathbb{E}_t\left(\left(r^{b,s}_{(t:t+\tau)} - \delta^{b,s}_t - \mathbb{E}_t(\tau)\mu^s_t\right)^k\right), \end{aligned} \tag{2.7}$$

where $U^{(k)}_\gamma(r) := \frac{\partial^k}{\partial r^k} U_\gamma(r)$.

Proof. See Appendix B.1. □

[3] The characteristic function fully describes the behavior and properties of a probability distribution. For a random variable X, $\varphi_X(u)$ is defined as $\varphi_X(u) = \mathbb{E}(e^{iuX})$, where i is the imaginary unit and $u \in \mathbb{R}$ is the argument of the characteristic function.

Theorem 1 allows us to compare the expected utility of making the arbitrage trade versus staying idle (which yields a riskless return of zero). The arbitrageur is willing to exploit cross-market price differences if and only if the CE of trading given by Equation (2.7) is positive. A positive CE corresponds to a statistical arbitrage opportunity in the sense of positive *expected* risk-adjusted profits. Whenever the observed price differences $\delta_t^{b,s}$ are positive but CE is negative, the arbitrageur does not trade. In this case, although the trade would be profitable under the possibility of instantaneous settlement, limits to (statistical) arbitrage arise due to stochastic latency. Hence, the arbitrageur is indifferent between trading and staying idle if the observed price differences $\delta_t^{b,s}$ imply $CE = 0$.

Definition 1. *We define the arbitrage bound d_t^s as the minimum price difference necessary such that the arbitrageur prefers to trade. Formally, d_t^s is the maximum of zero and the (unique) root[4] of*

$$\begin{aligned} F(d) =& d + \mathbb{E}_t(\tau)\mu_t^s \\ &+ \sum_{k=2}^{\infty} \frac{U_\gamma^{(k)}\left(d + \mathbb{E}_t(\tau)\mu_t^s\right)}{k! U_\gamma'\left(d + \mathbb{E}_t(\tau)\mu_t^s\right)} \mathbb{E}_t\left(\left(r_{(t:t+\tau)}^{b,s} - d - \mathbb{E}_t(\tau)\mu_t^s\right)^k\right). \end{aligned} \tag{2.8}$$

Price differences below the arbitrage bound d_t^s might persist as the arbitrageur prefers not to trade in such a scenario.

More intuitive representations of the arbitrage bound can be derived by assuming that the arbitrageur is equipped with absolute or relative risk aversion. In particular, we follow Schneider (2015) in ignoring the impact of higher order moments above the fourth degree of the Taylor representation in Equation (2.8) and assume that the price process has a drift of μ_t^s of zero. These two additional assumptions yield an analytically tractable formulation of the arbitrage bound. The following lemma gives the analytical closed-form expression for d_t^s under the assumption of a power utility function.

Lemma 5. *If, in addition to Assumptions 1 and 2, the arbitrageur has an isoelastic utility function $U_\gamma(r) := \frac{(1+r)^{1-\gamma}}{1-\gamma}$ with risk aversion parameter $\gamma > 1$, the arbitrage bound for $\mu_t^s = 0$*

[4] By definition of the CE, we have $F(d) = U_\gamma^{-1}\left(\mathbb{E}_t\left(U_\gamma\left(d + \mu_t^s \tau + \int_t^{t+\tau} \sigma_t^s W_k^s\right)\right)\right)$. Since $U_\gamma'(r) > 0$, the expectation is increasing in d. Moreover, since $U_\gamma''(r) < 0$, the inverse $U_\gamma^{-1}(r) > 0$ is also strictly concave. Thus, $F(d)$ is strictly increasing and has a unique root.

is given by

$$d_t^s = \frac{1}{2}\sigma_t^s \sqrt{\gamma \mathbb{E}_t(\tau) + \sqrt{\gamma^2 \mathbb{E}_t(\tau)^2 + 2\gamma(\gamma+1)(\gamma+2)\left(\mathbb{V}_t(\tau) + \mathbb{E}_t(\tau)^2\right)}}. \tag{2.9}$$

Proof. See Appendix B.1. □

Hence, d_t^s positively depends on (i) the arbitrageur's risk aversion γ, (ii) the local volatility on the sell-side market, σ_t^s, (iii) the (conditionally) expected waiting time until settlement, $\mathbb{E}_t(\tau)$, and (iv) the conditional variance of the waiting time, $\mathbb{V}_t(\tau)$. We show in Appendix B.4 that the special case of an exponential utility function with constant *absolute* risk aversion γ yields a similarly tractable expression.

The arbitrage bound obviously depends on the arbitrageur's risk aversion γ. Accordingly, for a risk-neutral arbitrageur, we have $d_t^s = 0$ and she would exploit any positive price difference $\delta_t^{b,s} > 0$. In this case, any price differences between the two markets should be absorbed immediately. Hence, in the absence of any other frictions, the existence of persistent price differences between two markets (which are not traded away) indicates that the markets are populated by risk-averse arbitrageurs who do not exploit price differences below the threshold d_t^s. We thus denote the interval $[0, d_t^s]$ as a *no-trade region* in which price differences between markets b and s are not exploited.[5]

The lower bound d_t^s is a fundamental pillar of markets with settlement latency, as the implied costs of settlement latency affect the entire action and contracting space of market participants. The only possibility to circumvent this latency would be the ability to sell *instantaneously* at the more expensive market to lock in the price difference. This is only possible, however, if the arbitrageur already has an inventory of the asset on the expensive (sell) market or if she can borrow the asset on that market. The first alternative bears considerable additional risks. To be able to exploit instantaneous price differences whenever they arise, arbitrageurs have to keep inventory on the sell-side market over longer periods. Only investors who do not require a premium for this inventory risk (e.g., due to hedging needs or diversification benefits) could act as risk-neutral arbitrageurs.[6] The second strategy requires that short-selling is offered by an

[5]The risk aversion is associated with the arbitrageur's attitude towards the risk of a single trade. Theoretically, repeatedly exploiting price differences may lead to a vanishing variance of the arbitrageurs' aggregate returns which is equivalent to a contraction of the relevant bounds. From an empirical perspective, however, high autocorrelation in the resulting individual returns due to the latency questions the feasibility of such a law of large numbers.

[6]In fact, anecdotal evidence suggests that investors in Bitcoin markets exert substantial effort to keep their inventory holdings at exchanges at a minimum to avoid exposure to any exchange-related

intermediary (e.g., the trading platform itself) and that margin constraints do not bind. The absence of central counterparties or trusted intermediaries, however, is likely to cause high costs of borrowing as the lack of trust manifests itself in substantial margin requirements to counterbalance counterparty risks. As a consequence, high margin requirements discourage market participants from circumventing latency-implied price risks. Our results thus characterize arbitrage bounds in a situation where inventory holdings or margins are exhausted and arbitrageurs are fully exposed to settlement latency. In this sense, we quantify the frictions that arise if trust and security of the settlement process are exclusively provided by a decentralized consensus mechanism.

2.3 Transaction Costs and Settlement Fees

Most markets request trading fees that agents pay upon the execution of a trade. For instance, traders frequently pay fees as a percentage of the trading volume when they execute trades on centralized exchanges. Similarly, broker-dealers usually charge markups for the execution of trades in over-the-counter markets. Moreover, markets typically exhibit limited supply in the form of price-quantity schedules that agents are willing to trade, possibly leading to substantial price impacts for large trading quantities. To incorporate trading fees and liquidity effects into our framework, we make the following assumption.

Assumption 4. *Trading the quantity $q \geq 0$ on market i exhibits proportional transaction costs such that the average per unit sell and buy quotes are*

$$B_t^i(q) = B_t^i \left(1 - \rho^{i,B}(q)\right) \tag{2.10}$$

$$A_t^i(q) = A_t^i \left(1 + \rho^{i,A}(q)\right), \tag{2.11}$$

with $\rho^{i,B}(q) \geq 0$ and $\rho^{i,A}(q) \geq 0$, both monotonically increasing in q.

The presence of transaction costs changes the objective function of the arbitrageur who

risks.

focuses on maximizing returns net of transaction costs defined as

$$\begin{aligned}\tilde{r}^{b,s}_{(t:t+\tau)} &= b^s_{t+\tau} - b^s_t + \delta^{b,s}_t - \log\left(\frac{1+\rho^{b,A}(q)}{1-\rho^{s,B}(q)}\right) \\ &= r^{b,s}_{(t:t+\tau)} - \log\left(\frac{1+\rho^{b,A}(q)}{1-\rho^{s,B}(q)}\right). \end{aligned} \tag{2.12}$$

From this expression immediately follows that transaction costs decrease the expected utility of the arbitrageur. A different interpretation of Equation (2.12) is that transaction costs only increase the instantaneous return required to make the arbitrageur indifferent between trading and staying idle. The following lemma summarizes the arbitrageur's decision problem in the presence of transaction costs.

Lemma 6. *Under assumptions 1–4, the arbitrageur prefers to trade a quantity $q > 0$ over staying idle if*

$$\delta^{b,s}_t - \log\left(\frac{1+\rho^{b,A}(q)}{1-\rho^{s,B}(q)}\right) > d^s_t. \tag{2.13}$$

Proof. See Appendix B.1. □

In addition to transaction costs, in distributed ledger systems, also settlement fees need to be taken into account. In such systems, validators typically receive a reward for confirming transactions. This reward (at least partly) comprises fees that originators of transactions offer to potential validators. Since the information that can be added to the ledger at any point in time is usually limited, such fees aim to provide validators with incentives to prioritize the settlement of transactions that include a higher fee (see, e.g., Easley et al., 2019). By offering a higher fee, arbitrageurs can thus decrease the settlement latency they face. We extend our framework to incorporate such latency-reducing settlement fees as follows.

Assumption 5. *A settlement fee $f > 0$ implies a latency distribution $\pi_t(\tau|f)$ that can be ordered in the sense that for $\tilde{f} > f$, $\pi_t(\tau|f)$ first-order stochastically dominates $\pi_t\left(\tau|\tilde{f}\right)$, that is, $\mathbb{P}\left(\tau \leq x|\tilde{f}\right) > \mathbb{P}(\tau \leq x|f)$ for all $x \in \mathbb{R}_+$.*

The ordering of latency distributions in Assumption 5 implies a lower CE of trading for $\tilde{f} > f$.[7] Denote by $d^s_t(f)$ the arbitrage bound associated with the latency distribution $\pi_t(\tau|f)$. Theorem 1 then implies that $d^s_t(f) > d^s_t(\tilde{f})$, that is, by paying a higher

[7]We refer to Hadar and Russell (1969) and Levy (1992) for an explicit analysis of the relation between stochastic dominance and expected utility.

settlement fee, the arbitrageur can reduce the risk associated with settlement latency and becomes more likely to trade. For simplicity, we assume that $d_t^s(f)$ is differentiable such that Assumption 5 implies $\frac{\partial}{\partial f} d_t^s(f) < 0$.

While settlement fees reduce the latency, they are costly for the arbitrageur. Since the arbitrageur does not hold inventory of the asset on the buy-side market, she has to acquire the additional quantity f to spend it in the settlement process. In line with practical implementation in most systems, where cryptocurrencies are transferred, we assume that the arbitrageur has to pay the settlement fee in terms of the underlying asset. Given the transaction costs from above, the choice of f thus also affects the trading quantity q. The following lemma characterizes the arbitrageur's decision problem in the presence of transaction costs and settlement fees.

Lemma 7. *Under assumptions 1–5, the arbitrageur prefers to trade a quantity $q > 0$ and pay a settlement fee $f > 0$ over staying idle if*

$$\delta_t^{b,s} - \log\left(\frac{1 + \rho^{b,A}(q + f)}{1 - \rho^{s,B}(q)}\right) > d_t^s(f). \tag{2.14}$$

Proof. See Appendix B.1. □

Trading a larger quantity might deliver higher total returns, but it comes at the cost of higher transaction costs on both the buy-side and sell-side markets. Moreover, paying higher settlement fees leads to lower arbitrage bounds but at the cost of additional transaction costs on the buy-side market. The arbitrageur's trading decision thus features a trade-off between q and f with endogenous arbitrage bounds. Formally, the arbitrageur aims to maximize total returns

$$\max_{\{q,f\} \in \mathbb{R}_+^2} B_t^s \left(1 - \rho^{s,B}(q)\right) q - A_t^b (1 + \rho^{b,A}(q + f))(q + f) \tag{2.15}$$

subject to the constraint

$$\delta_t^{b,s} - \log\left(\frac{1 + \rho^{b,A}(q + f)}{1 - \rho^{s,B}(q)}\right) \geq d_t^s(f). \tag{2.16}$$

We characterize the arbitrageur's optimal choice of trading quantities and settlement fees in the following lemma.

Lemma 8. *A total return maximizing arbitrageur only pays a settlement fee* $f^* > 0$ *to trade a quantity* $q^* > 0$ *if the following necessary conditions are met:*

$$\frac{1 - \rho^{s,B}(q^*)}{q^*} > \frac{\partial}{\partial q}\rho^{s,B}(q^*) \tag{2.17}$$

$$-\frac{\partial}{\partial f}d_t^s(f^*) > \frac{\frac{\partial}{\partial q}\rho^{s,B}(q^*)}{1 + \rho^{s,B}(q^*)}. \tag{2.18}$$

Otherwise, the arbitrageur optimally sets $f^* = 0$*. Moreover, a total return maximizing arbitrageur chooses trading quantities* $q^* > 0$ *and settlement fees* $f^* \geq 0$ *such that*

$$\delta_t^{b,s} - \log\left(\frac{1 + \rho^{b,A}(q^* + f^*)}{1 - \rho^{s,B}(q^*)}\right) = d_t^s(f^*). \tag{2.19}$$

Proof. See Appendix B.1. □

The first part of the lemma provides conditions for choosing the settlement fee. According to Equation (2.17), the arbitrageur chooses a positive settlement fee as long as the marginal price impact for the trading quantity is below the average price impact. However, Equation (2.18) shows that the reduction of the arbitrage bound through a higher settlement fee must exceed the implied opportunity costs, that is, the possible gain in selling a higher quantity. As a consequence, the arbitrageur tends to pay a higher settlement fee if the sell-side market is very liquid (keeping the marginal price impact low) and the settlement fee has a high impact on the arbitrage bound (i.e., reducing the latency and thus risk). If any of these two conditions is violated, the arbitrageur optimally chooses not to pay any settlement fee but might still decide to trade.

The second part of the lemma states that the arbitrageur always chooses trading quantities and settlement fees such that the constraint in Equation (2.16) binds. If the constraint were not binding, the arbitrageur could trade a larger quantity to increase her total returns at the expense of higher transaction costs.

2.4 Bitcoin Order Book and Network Data

2.4.1 Bitcoin Order Book Data

We gathered order book information from the public application programming interfaces (APIs) of the 16 largest cryptocurrency exchanges that feature BTC versus USD trading.[8] We retrieved all open buy and sell orders for the first 25 levels on a minute interval from January 1, 2018, to October 31, 2019. The granularity of our data yields detailed information on order book depth.[9]

Table 2.1 gives the corresponding exchanges and provides summary statistics of the underlying order book data of our sample period. We observe a strong heterogeneity of exchange-specific liquidity. For instance, whereas investors could have traded BTC versus USD at *Coinbase Pro* with an average spread of 0.45 USD, the average quoted spread at *Gatecoin* has been about 337 USD since January 2018. For most exchanges, however, the relative bid-ask spreads are comparable to those from equity markets such as Nasdaq or NYSE, where relative spreads range from 5 basis points (bp) for large firms to 38 bp for small firms (e.g., Brogaard et al., 2014).

The exchanges also exhibit substantial heterogeneity in terms of trading-related characteristics. Taker fees range from 0% on *Lykke* to 1% on *Gemini*. Another potential transaction cost are withdrawal fees that have to be paid upon the transfer of BTC from the exchange to any other exchange or private address. Exchanges charge up to 0.003 BTC for withdrawal requests, which corresponds to roughly 30 USD in prices as of April 2018, irrespective of the withdrawn amount. Furthermore, exchanges have different requirements with respect to the number of block confirmations before they proceed to process BTC deposits. For instance, *Kraken* requires that incoming transactions must be included in at least 6 blocks. The objective of these requirements is to reduce the possibility of an attack that aims at revoking previous transactions, that is, a so-called 'double-spending attack'. In such a scenario, a potential attacker has to alter all blocks containing the corresponding transaction. The probability that an attacker catches up with the honest chain decreases exponentially with the number of blocks the attacker has to alter. For instance, in the case of a confirmation requirement of 10 blocks, the probability of a successful attack is less than 0.01% (5%), if the attacker has

[8]Some exchanges do not feature fiat currencies. However, they allow trading BTC against Tether, a token that is backed by one USD for each token and trading close to par with USD.

[9]To the best of our knowledge, none of these exchanges offers the opportunity to place hidden orders. Our data set thus reflects a real-time image of the available liquidity on each exchange.

Table 2.1: Descriptive Statistics of the Order Book Sample

	Order Books	Spread (USD)	Spread (bp)	Taker Fee	With. Fee	Conf.	Margin	Business
Binance	941,399	2.61	3.29	0.10	0.00100	2	✓	✗
Bitfinex	938,703	0.62	0.74	0.20	0.00080	3	✓	✓
bitFlyer	919,182	15.13	20.52	0.15	0.00080		✓	✓
Bitstamp	938,483	5.11	6.33	0.25	0.00000	3	✗	✓
Bittrex	940,523	9.07	13.20	0.25	0.00000	2	✗	✓
CEX.IO	936,378	11.73	15.07	0.25	0.00100	3	✓	✓
Gate	907,874	81.24	90.92	0.20	0.00200	2	✗	✗
Gatecoin	560,111	336.52	515.87	0.35	0.00060	6	✗	✓
Coinbase Pro	941,539	0.45	0.54	0.30	0.00000	3	✓	✓
Gemini	912,944	2.57	3.40	1.00	0.00200	3	✗	✓
HitBTC	919,686	2.96	3.68	0.10	0.00085	2	✗	✗
Kraken	936,970	2.63	3.24	0.26	0.00100	6	✓	✓
Liqui	491,516	30.15	45.13	0.25			✓	✗
Lykke	918,768	44.04	57.95	0.00	0.00050	3	✗	✗
Poloniex	916,876	5.38	7.51	0.20		1	✓	✗
xBTCe	887,289	13.34	17.87	0.25	0.00300	3	✓	✗

Notes: This table reports descriptive statistics of order book data used in our study. We gathered high-frequency order book information of 16 exchanges by accessing the public application programming interfaces (APIs) every minute. *Order Books* denotes the number of successfully retrieved order book snapshots between January 1, 2018 and October 31, 2019. *Spread (USD)* is the average quoted spread in USD, *Spread (bp)* is the average spread relative to the quoted best ask price (in basis points). *Taker Fee* is the associated trading fee in percentage points relative to the trading volume. *With. Fee* referes to the withdrawal fee in BTC. *Conf.* refers to the number of blocks that the exchange requires to consider incoming transactions as being valid. Empty cells indicate missing values. *Margin* refers to the existence of BTC shorting instruments at the exchange. *Business* indicates whether the exchange allows business accounts and hence access to institutional investors.

a share of 30% (10%) of the total available computing power (Nakamoto, 2008). As we discuss below, these requirements confront arbitrageurs with a mechanical increase in settlement latency.

Finally, we collected information about two exchange characteristics that might help arbitrageurs to circumvent the exposure to settlement latency. On the one hand, some exchanges offer margin trading instruments which allow traders to short BTC and avoid settlement latency. However, such margin trading always comes at the cost of substantial collateral deposits which the exchanges control. On the other hand, some exchanges allow businesses to open an account which provides institutional investors with the opportunity to hold inventories and exploit price differences. Holding inventories at exchanges is costly though, since it is associated with continuous exposure to fluctuations in prices and exchange-specific default or hacking risks. However, as we demonstrate in Section 2.6, the mere presence of margin trading instruments or access for institutional investors is not a sufficient condition to completely offset the impact of settlement latency.

2.4.2 Bitcoin Network Data

We gathered transaction-specific information from blockchain.com, a popular provider of Bitcoin network data. We downloaded all blocks verified between January 1, 2018, and October 31, 2019, and extracted information about all verified transactions in this period. Each transaction contains a unique identifier, a timestamp of the initial announcement to the network, and, among other details, the fee (per byte) the initiator of the transaction offers validators to verify the transaction.[10]

Any transaction in the Bitcoin network, irrespective of its origin, has to go through the so-called *mempool* which is a collection of all unconfirmed transactions. These transactions wait until they are picked up by validators and get verified. The size of the mempool thus reflects the number of transactions that wait for confirmation. By design, the Bitcoin protocol restricts the number of transactions that can enter a single block. This restriction induces competition among the originators of transactions who can offer higher settlement fees to make including transactions in the next block attractive to validators. Consequently, transactions with no or very low settlement fees may not attract validators and thus stay in the mempool until they become verified eventually.[11]

Validators bundle transactions that wait for verification and try to solve a computationally expensive problem which involves numerous trials until the first validator finds the solution. By design of the Bitcoin protocol, validators successfully find a solution and append a block on average every 10 minutes (during our sample period, new blocks are announced to the network on average every 9.7 minutes). The time until verification, however, should not be confused with the time it takes until a new block is mined. Even though the expected block validation time is 10 minutes, it is ex-ante uncertain when a transaction is included in a block for the first time. The number of outstanding transactions serves as a proxy for fluctuations in congestion of the Bitcoin network. Whereas on average 1,644 transactions per block have been included in our sample period, the average number of transactions in the mempool is above 10,000 with temporary peaks of more than 41,000 transactions waiting for verification. For any transaction this induces stochastic settlement latency. The probability of be-

[10] The fee per byte is more relevant than the total fee associated with a transaction as block sizes are limited in terms of bytes. In principle, a transaction can have multiple inputs and outputs, that is, several addresses that are involved as senders or recipients of a transaction, which increases the number of bytes.

[11] Relaxing this artificial supply constraint might reduce issues pertaining to settlement latency but at the cost of network security (e.g., Hinzen et al., 2019).

Table 2.2: Descriptive Statistics of Transactions in the Bitcoin Network

	Mean	SD	5%	25%	Median	75%	95%
Fee per Byte (in Satoshi)	47.41	183.08	1.21	5.00	14.06	45.52	200.25
Fee per Transaction (in USD)	1.98	24.19	0.02	0.09	0.28	1.12	7.54
Latency (in Min)	41.03	289.26	0.73	3.55	8.82	20.75	109.52
Mempool Size (in Number)	10,018.74	14,876.52	432.00	1,812.00	4,503.50	11,057.50	41,884.50
Transaction Size (in Bytes)	507.28	2174.13	192.00	225.00	248.00	372.00	958.00

Notes: This table reports descriptive statistics of the Bitcoin transaction data used in our study. The sample contains all transactions settled in the Bitcoin network from January 1, 2018, to October 31, 2019. Our sample comprises 139,704,737 transactions that are verified in 99,129 blocks. *Fee per Byte* is the total fee per transaction divided by the size of the transaction in bytes in Satoshi where 100,000,000 Satoshi are 1 Bitcoin. *Fee per Transaction* is the total settlement fee per transaction (in USD). We approximate the USD price by the average minute-level midquote across all exchanges in our sample. *Latency* is the time until the transaction is either validated or leaves the mempool without verification (in minutes). *Transaction Size* denotes the size of a transaction in bytes. *Mempool Size* is the number of other transactions in the mempool at the time a transaction of our sample enters the mempool.

ing included in the next block decreases with the number of transactions that wait for settlement and increases with the settlement fee the investor is willing to pay.

Table 2.2 provides summary statistics of the recorded transactions. The average settlement fee per transaction is about 2 USD. The distribution of fees exhibits a strong positive skewness with a median of 0.28 USD. The average waiting time until the verification of a transaction is about 41 minutes, while the median is about 8.8 minutes.

2.4.3 Price Differences Across Markets

To provide systematic empirical evidence on the extent of potential arbitrage opportunities and thus violations of the law of one price, we compute the observed instantaneous cross-market price differences, adjusted for transaction costs, of all 120 exchange pairs (with the total number of exchanges $N = 16$), defined as

$$\tilde{\Delta}_t := \begin{pmatrix} 0 & \cdots & \tilde{\delta}_t^{N,1} \\ \vdots & \ddots & \vdots \\ \tilde{\delta}_t^{1,N} & \cdots & 0 \end{pmatrix} = \begin{pmatrix} 0 & \cdots & \tilde{b}_t^1\left(q_t^{N,1}\right) - \tilde{a}_t^N\left(q_t^{N,1}\right) \\ \vdots & \ddots & \vdots \\ \tilde{b}_t^N\left(q_t^{1,N}\right) - \tilde{a}_t^1\left(q_t^{1,N}\right) & \cdots & 0 \end{pmatrix}, \quad (2.20)$$

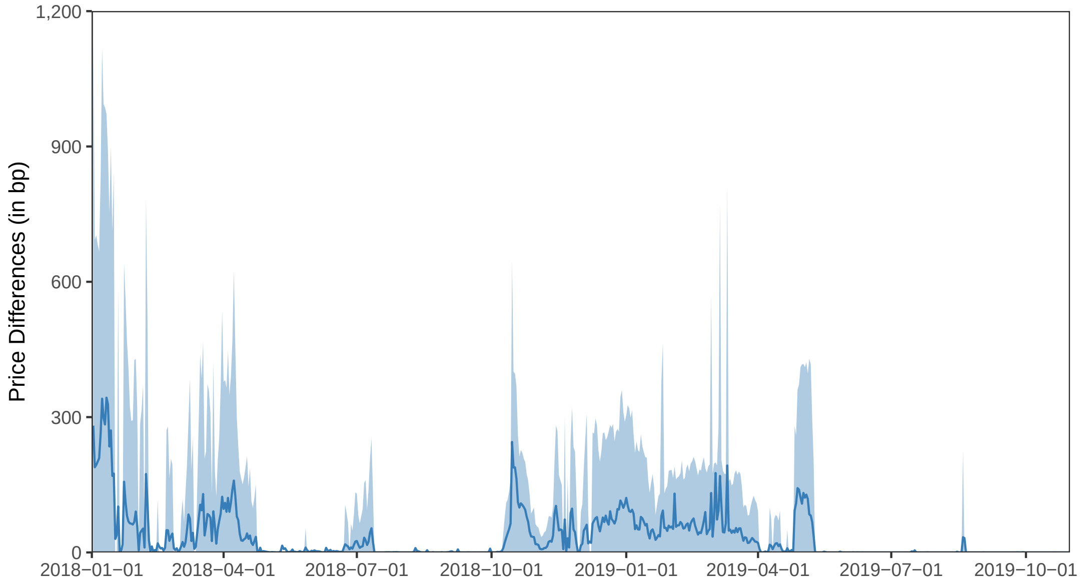
where $\tilde{b}_t^i(q_t^{i,j})$ is the transaction cost-adjusted (log) sell price of $q_t^{i,j}$ units of the asset on exchange i at time t, and $\tilde{a}_t^i(q_t^{i,j})$ is the transaction cost-adjusted (log) buy price of $q_t^{i,j}$ units of the asset. For analyses in which we abstract from transaction costs, we use the best bid and ask quotes of each exchange.

In line with our definition in Section 2.3, transaction costs are proportional to the trading quantity. We choose $q_t^{i,j}$ as the quantity that maximizes the resulting return for the exchange pair i and j given the prevailing order books at time t, the taker fees of exchanges i and j and withdrawal fees of exchange j. Accordingly, we account for proportional exchange-specific taker fees (as reported in Table 2.1), which increase the average buy price and decrease the average sell price. We then use the resulting transaction cost-adjusted order book queues and apply a grid search algorithm to identify the trading quantity that maximizes the total return for each exchange pair. As a last step, we check if the resulting trading quantity exceeds the withdrawal fee that the buy-side exchange charges for outgoing transactions (see Table 2.1). If the optimal trading quantity is below the withdrawal fee, we set the trading quantity to zero. This data-driven approach thus mimics the strategy of an arbitrageur who aims to maximize profits by optimally accounting for the prevailing order book depth and other trading-related fees. As price differences obviously can only be positive in one trading direction, we set negative price differences to zero as such scenarios (even without latency) do not correspond to arbitrage opportunities. The resulting matrix of price differences thus contains only non-negative values.

Figure 2.2 depicts the daily average of minute-level price differences based on optimal trading quantities according to Equation (2.20) across all exchange pairs. We observe a substantial variation over time. The average daily price difference across all exchange pairs is on average 33 bp. The 90% quantile is on average 129 bp, indicating a large dispersion of price differences through our sample period.

Figure 2.3 shows the average price differences for each exchange pair. The heatmap shows that some exchanges exhibit quotes that tend to deviate quite systematically from (nearly) all other exchanges. For instance, *Bitfinex*, *CEX.IO*, *Gatecoin* and *HitBTC* quote on average higher bid prices than most other exchanges and thus exhibit large price differences when used as a sell-side market. Conversely, other exchange pairs do not feature large average price differences. For instance, there are hardly any price differences whenever *Coinbase Pro* or *Kraken* serve as sell-side markets.

Figure 2.2: Price Differences over Time



Notes: This figure shows the daily average of price differences adjusted for transaction costs $\tilde{\delta}_t^{b,s}$, across all exchange pairs from January 1, 2018, to October 31, 2019. Price differences are based on minute-level transaction cost-adjusted bid and ask quotes for each exchange according to Equation (2.20). We account for exchange-specific taker fees according to Table 2.1 and compute the quantity which maximizes the return for each exchange pair using a grid search algorithm. The shaded area indicates the 10% and 90% quantiles of price differences on a given day.

2.5 Quantifying Arbitrage Bounds

2.5.1 Spot Volatility Estimation

To estimate the spot volatility, we follow the approach of Kristensen (2010). For each market s and minute t, we estimate $(\sigma_t^s)^2$ by

$$\widehat{(\sigma_t^s)}^2(h_T) = \sum_{l=1}^{\infty} K(l-t, h_T)\left(b_l^s - b_{l-1}^s\right)^2, \tag{2.21}$$

where $K(l-t, h_T)$ is a one-sided Gaussian kernel smoother with bandwidth h_T and b_l^s corresponds to the quoted bid price on market s at minute l. The choice of the bandwidth h_T involves a trade-off between the variance and the bias of the estimator. Considering too many observations introduces a bias if the volatility is time-varying, whereas shrinking the estimation window through a lower bandwidth results in a higher variance of the estimator. Kristensen (2010) thus proposes to choose h_T such

Figure 2.3: Price Differences between Exchanges

Notes: The heatmap shows the average price differences, adjusted for transaction costs, $\tilde{\delta}_t^{b,s}$, across time for each exchange pair in our sample. Price differences are based on minute-level transaction cost-adjusted bids and asks for each exchange according to Equation (2.20). We account for exchange-specific taker fees according to Table 2.1 and compute the quantity which maximizes the return for each exchange pair using a grid search algorithm. The darker the color, the higher the average price difference through our sample period in the specific exchange pair. White or very light colors indicate that there are on average no or few price differences for a specific exchange pair.

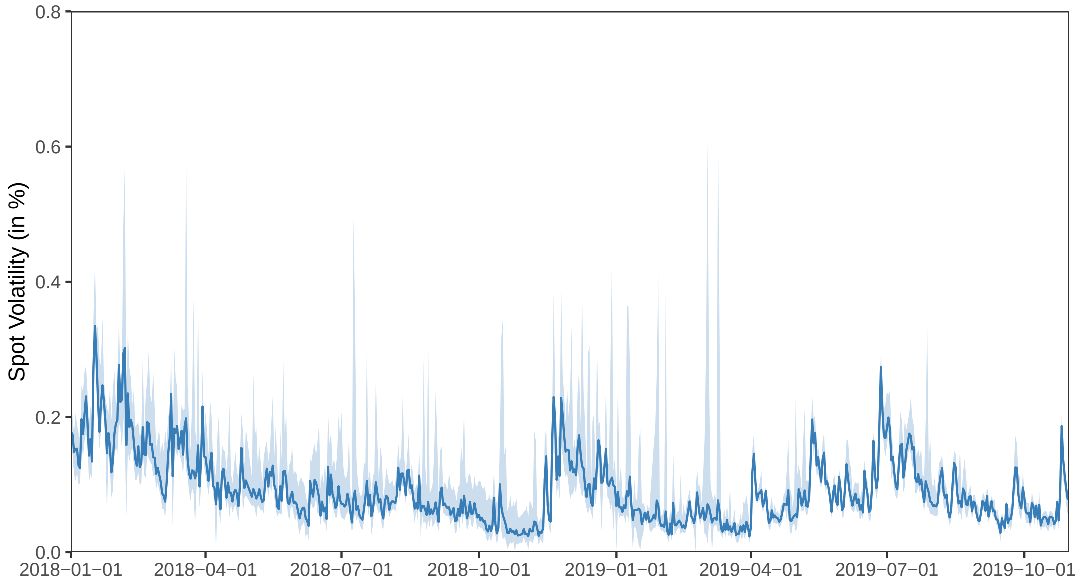
that information on day $T-1$ is used for the estimation on day T. Formally, the bandwidth on any day of our sample is the result of minimizing the Integrated Squared Error (ISE) of estimates on the previous day, that is,

$$h_T = \arg\min_{h>0} \sum_{l=1}^{1440} \left[\left(b_l^s - b_{l-1}^s \right)^2 - \widehat{\left(\sigma_l^s \right)}^2 (h) \right]^2 , \tag{2.22}$$

where l refers to the minutes on day $T-1$ and $\widehat{\left(\sigma_l^s \right)}^2 (h)$ is the spot variance estimator for minute l on day $T-1$ based on bandwidth h.

For each exchange, we trim the distribution of all estimates at 1% on both tails to eliminate outliers (e.g., due to flickering quotes). Figure 2.4 displays the cross-market average of spot volatility estimates on a daily basis. Since the underlying asset is identical, the resulting estimates—as expected—do not differ substantially across exchanges. The average minute-level volatility across exchanges is about 0.09%, which

Figure 2.4: Time Series of Spot Volatility Estimates



Notes: This figure shows the daily cross-market average of minute-level spot volatility estimates from January 1, 2018, to October 31, 2019. For each exchange, we estimate minute-level spot volatilities as the time-weighted average of squared bid price changes with a one-sided Gaussian kernel (Kristensen, 2010). For each day, we compute the average volatility across all exchanges. The shaded area corresponds to the range of average daily exchange-specific volatility estimates.

translates into a daily volatility of about 3.4%, significantly higher than the average daily volatility of the S&P 500 index during the same period, which yields roughly 0.65%.[12]

2.5.2 Latency Prediction

We use all verified transactions to parametrize the latency in the settlement process of the Bitcoin blockchain. In line with Chiu and Koeppl (2019) and Easley et al. (2019) we expect that transaction fees and mempool congestion play an important role in the determination of the expected time until verification. Accordingly, we employ a gamma regression where the conditional probability density function of latency τ_i

[12]We convert minute-level estimates to the daily level by multiplying it with the square root of the number of minutes on any given trading day, that is, $\sqrt{1440}$.

with rate parameter β_i and shape parameter α_T is given by

$$\pi(\tau_i|\theta_T) = \frac{\beta_i^{\alpha_T}}{\Gamma(\alpha_T)} \tau_i^{\alpha_T - 1} e^{-\beta_i \tau_i}, \tag{2.23}$$

where

$$\theta_T := (\theta_T^\beta, \alpha_T)' \in \mathbb{R}^k \text{ and } \beta_i = \exp(-x_i' \theta_T^\beta), \alpha_T > 0. \tag{2.24}$$

Here, $x_i \in \mathbb{R}^K$ includes an intercept and denotes (pre-determined) covariates driving τ_i, $\theta_T^\beta \in \mathbb{R}^K$ denotes the corresponding vector of parameters and $\Gamma(x) := \int_{\mathbb{R}_+} z^{x-1} e^{-z} dz$ is the Gamma function. The gamma distribution collapses to an exponential distribution for $\alpha_T = 1$. We estimate the parameter vector θ_T using all verified transactions on day $T-1$ via maximum likelihood, both with and without covariates. In addition, we estimate an exponential model by fixing $\alpha_T = 1$. As covariates x_i, we include settlement fees and the (log) size of the mempool. The settlement fees enter as *fees per byte* as the relevant metric for validators who face a restriction in terms of the maximum size of a block in bytes. The number of transactions waiting for verification at the time when a transaction is announced serves as a proxy for competition among transactions.

In Table 2.3, we provide summary statistics of the estimated parameters. The numbers in the brackets denote the 5% and 95% quantiles of the time series of estimated parameters. The marginal effect of settlement fees is statistically significant and has the expected sign for nearly all days, that is, higher fees predict a lower latency. The mempool size exhibits a positive impact on latencies through our sample period, that is, congestion of the mempool decreases the probability of inclusion of a transaction in the next block (see, e.g., Huberman et al., 2017; Easley et al., 2019). A likelihood ratio test against a model without covariates indicates that the regressors are jointly highly significant. We therefore find clear evidence that the waiting time until a transaction enters the next block of the blockchain is predictable. We moreover find that the exponential distribution is rejected in favor of the more general gamma distribution in nearly 93% of all days.

To predict the (conditional) moments of the latency distribution while avoiding any look-ahead bias, we use the estimated parameter $\hat{\theta}_T$ based on transactions from day $T-1$ to parameterize the latency distribution for every minute t of day T. We provide further direct evidence for the predictability of settlement latency by computing the in-sample as well as out-of-sample root mean square prediction errors (MSPEs). In particular, for the in-sample MSPE, we use all transactions that feed into the estimation of $\hat{\theta}_T$ (i.e., all transactions verified on day $T-1$). The out-of-sample MSPE is based on predictions for all transactions verified on day T using the estimated parameter vector $\hat{\theta}_T$. We find that the in-sample MSPE is on average smaller for the unrestricted model specifications and that the unrestricted models exhibit on average a lower out-of-sample MSPE compared to their restricted counterparts. As a consequence, we predict the latency using the unrestricted Gamma model.

Accordingly, the conditional mean and variance of the latency τ, induced by a transaction at minute t on day T with characteristics x_t, is given by

$$\widehat{\mathbb{E}}_t(\tau) = \hat{\alpha}_T \exp(x_t'\hat{\theta}_T^{\beta}), \qquad \text{and} \qquad \widehat{\mathbb{V}}_t(\tau) = \hat{\alpha}_T \exp(2x_t'\hat{\theta}_T^{\beta}), \tag{2.25}$$

where x_t consists of the mempool size and the fee an arbitrageur is willing to pay at time t. While the mempool size is observable at any point in time, we use the optimal fee as derived in Lemma 8 as a proxy for the individually chosen settlement fees.

2.5.3 Estimation of Arbitrage Bounds

Based on the empirically relevant CRRA case of Lemma 5, the estimated arbitrage bounds $\hat{d}_t^s$ at minute t are given by

$$\hat{d}_t^s = \frac{1}{2}\hat{\sigma}_t^s\sqrt{\gamma m_1 + \sqrt{\gamma^2 m_1^2 + 2\gamma(\gamma+1)(\gamma+2)m_2}}, \tag{2.26}$$

with

$$m_1 = \widehat{\mathbb{E}}_t(\tau) + \widehat{\mathbb{E}}_t(\tau_B)\cdot(B^s - 1), \tag{2.27}$$

$$m_2 = \widehat{\mathbb{V}}_t(\tau) + \widehat{\mathbb{V}}_t(\tau_B)\cdot(B^s-1)^2 + \Big(\widehat{\mathbb{E}}_t(\tau_B)\cdot(B^s-1) + \widehat{\mathbb{E}}_t(\tau)\Big)^2, \tag{2.28}$$

where $\hat{\sigma}_t^s$ denotes the square root of the estimated spot volatility on the sell-side exchange, and $\widehat{\mathbb{E}}_t(\tau)$ and $\widehat{\mathbb{V}}_t(\tau)$ denote the estimated conditional mean and variance of the latency distribution, respectively. Moreover, B^s refers to the number of blocks that the sell-side exchange s requires to consider incoming transactions as valid (see Table 2.1). This exchange-specific security requirement thus further increases the settlement

Table 2.3: Parameter Estimates for the Duration Models

	Exponential		Gamma	
	w/o Covariates	w/ Covariates	w/o Covariates	w/ Covariates
Intercept	3.31 [2.510, 4.246]	1.41 [-0.070, 3.675]	3.86 [2.626, 5.250]	1.19 [0.013, 2.596]
α			0.62 [0.358, 0.902]	0.63 [0.365, 0.900]
Fee per Byte		-0.22 [-0.486, -0.031]		-0.22 [-0.501, -0.031]
Mempool Size		0.23 [-0.043, 0.452]		0.31 [0.059, 0.530]
LR (Covariates)	91.33		74.59	
LR (Gamma vs. Exponential)	92.68			
MSPE (In-Sample)	65.67	65.74	65.67	66.02
MSPE (Out-of-Sample)	70.97	70.81	70.97	70.55

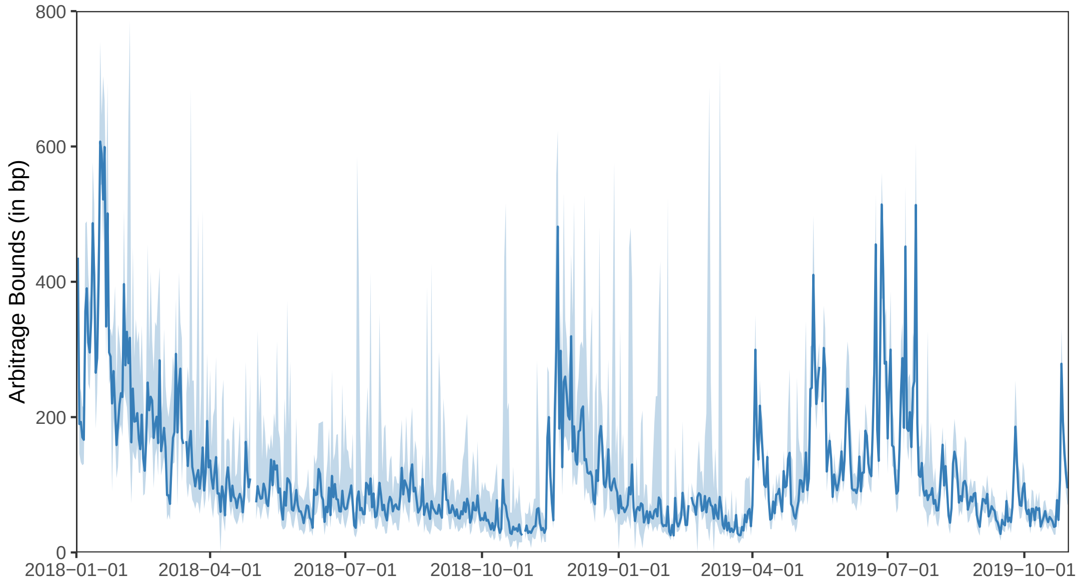
Notes: This table reports summary statistics for the estimated parameters of the gamma duration model given by Equation (2.23). *Fee* denotes fee per byte and *Mempool Size* refers to the number of unconfirmed transactions in the mempool. We estimate each model for each day in our sample, where we consider all transactions confirmed on a particular day. We report the time series averages of the estimated parameters. Values in brackets correspond to the 5% and 95% percent quantiles of the estimated parameters. *LR (Covariates)* summarizes likelihood ratio tests of the corresponding unrestricted duration model *with* covariates against the restricted model *without* covariates. *LR (Gamma vs. Exponential)* summarizes likelihood ratio tests of the gamma duration model against the exponential specification. The reported values denote the percentage of days where the null hypothesis that the likelihood of the more general model equals the likelihood of the restricted model is rejected at the 95% significance level. *MSPE* refers to the mean squared prediction error for out-of-sample and in-sample tests, respectively.

latency beyond the waiting time until a transaction's validation in the first block.[13]

We thus decompose the latency into two components: the time it takes until a transaction is included in the blockchain (i.e., the first block), τ, and the additional time until exchanges accept the transaction as being de facto immutable. While τ is partially under the control of the arbitrageur, the validation time of subsequent blocks is exogenous. In fact, we do not find evidence against non-zero autocorrelation in waiting times and constant volatility in the block validation time. This evidence supports the notion that the validation times of blocks are partially under control of the Bitcoin network and are internally impaired by the computational complexity of the underlying cryptographic problem. As a result, we can safely assume that the waiting times between subsequent blocks after the first one, which includes the current transaction,

[13] *bitFlyer* and *Liqui* do not report a minimum number of confirmations. They rather use a discretionary system depending on the individual transaction and the state of the network. In this case, we assume the number of confirmations to be equal to the median across all exchanges that provide such information, which is 3.

Figure 2.5: Estimated Arbitrage Bounds over Time



Notes: This figure shows the daily average estimated arbitrage bound based on a CRRA utility function with risk aversion parameter $\gamma = 2$ from January 1, 2018, to October 31, 2019. We estimate the bounds using spot volatility estimates following Kristensen (2010) and out-of-sample predictions of the conditional moments of the latency based on a gamma duration model. The solid blue line shows the daily averages (in basis points) across all exchanges. The shaded area corresponds to the range of daily exchange-specific averages.

are independently and identically distributed. As validators append a new block on average every 9.7 minutes in our sample, we use this magnitude as the best possible prediction of the time between two subsequent blocks, $\widehat{\mathbb{E}}_t\left(\tau_B\right)$. Accordingly, $\widehat{\mathbb{V}}_t\left(\tau_B\right)$ denotes the (sample) variance of the time between two consecutive blocks.

We fix the coefficient of risk aversion to $\gamma = 2$ and estimate $\hat{d}_t^s$ for each exchange on a minute level.[14] As shown by Figure 2.5, we observe substantial variation of these bounds over time. Arbitrage bounds are large especially during phases of high price volatility. We cannot reject the null hypothesis that the correlation between volatility and expected latency is significantly different from zero, which suggests that settlement latency constitutes a source of risk not captured by price fluctuations.

Table 2.4 gives summary statistics of the resulting time series of arbitrage bounds. We observe that these bounds range, on average, between 91 bp and 197 bp. While the conditional moments of the latency distribution affect the time series variation of the

[14]Our calibration follows Conine et al. (2017), who estimate an average coefficient of relative risk aversion of about 2 over an extensive sample period.

bounds, the cross-sectional variation is driven by the exchange-specific spot volatilities and the required number of confirmations, B^s. For instance, *Gatecoin* and *Kraken* require $B^s = 6$ confirmations and produce on average the highest bounds, while *Poloniex* requires only $B^s = 1$ confirmation yielding the smallest median bound. To quantify the effect of the exchange-specific security component B^s, we decompose the arbitrage bounds into the component resulting from the latency until a transaction is included in a block for the first time, τ, and the component resulting from the waiting time until a transaction fulfills exchange-specific security requirements, $(B^s - 1)\tau_B$. The second to last column in Table 2.4 gives the increase in the median arbitrage bound when we take the exchange-specific number of confirmations into account. The values correspond to the (percentage) difference between the median arbitrage bound as of Equation (2.26) and the respective bounds based on the assumption $B^s = 1$ for all exchanges. We observe that the impact of exchange-specific security components on arbitrage bounds is substantial and accounts on average for 23% of the bounds.

To shed more light on the implied costs of decentralized settlement under sufficiently high security standards, we quantify the relation between the level of security and the resulting latency. For each exchange, we compute arbitrage bounds for a given hypothetical number of confirmations and compare it to the baseline case of no additional security requirements (i.e., whenever the inclusion in the first upcoming block is sufficient). As a result, we find that requiring 10 confirmations at all exchanges (high security) would yield average arbitrage bounds of 175 bp, whereas the average bound when requiring only 1 confirmation (low security) would be 101 bp. The resulting difference between requiring 1 confirmation and 10 confirmation hence amounts to more than 73%. This analysis shows how security in a distributed ledger translates into settlement latency which in turn materializes into 7 bp of no-arbitrage regions per additional block.

Moreover, our theoretical framework allows us to directly analyze the relevance of the latency *uncertainty*. As the uncertainty of the arbitrageurs' returns increases with the variance of the settlement latency, we can compare the estimated arbitrage bounds to the (hypothetical) case of a *deterministic* latency. The last column in Table 2.4 reports the percentage increase in arbitrage bounds when adjusting for the randomness in latency. The values correspond to the percentage difference between the median arbitrage bound and bounds based on the assumption $\mathbb{V}_t(\tau) = \mathbb{V}_t(\tau_B) = 0$. We find that the impact of the randomness in latency is substantial and accounts on average for 41% of the arbitrage bounds.

Table 2.4: Summary of Exchange-Specific Arbitrage Bounds

	Mean	SD	5%	25%	Median	75%	95%	Security	Uncertainty
Binance	114.75	318.76	24.35	42.10	68.92	125.59	320.28	13.54	41.53
Bitfinex	117.22	299.25	18.89	42.47	73.26	136.19	324.19	23.98	40.85
bitFlyer	130.85	317.68	33.02	57.07	86.62	145.18	333.88	24.09	40.72
Bitstamp	126.34	294.72	28.45	50.53	80.46	145.61	341.72	23.69	40.79
Bittrex	129.03	277.80	30.94	57.25	89.41	143.51	333.37	14.32	41.63
CEX.IO	120.84	286.39	29.46	52.72	81.69	136.05	305.50	24.44	40.60
Gate	101.50	277.20	24.12	43.81	68.78	117.27	260.03	14.04	41.48
Gatecoin	196.89	219.90	2.62	46.70	118.29	274.82	638.77	45.95	40.26
Coinbase Pro	114.84	305.25	17.89	40.75	71.77	132.79	318.48	24.44	40.68
Gemini	115.36	343.30	21.07	43.27	72.42	130.54	309.53	24.44	40.77
HitBTC	101.22	287.97	19.10	37.64	62.72	112.79	273.14	14.14	41.36
Kraken	135.07	271.66	25.37	54.09	91.53	164.15	357.11	41.86	40.50
Liqui	90.79	60.20	23.51	49.96	77.40	115.62	201.88	28.97	39.98
Lykke	133.43	379.31	18.58	44.51	80.57	150.73	381.17	25.21	40.61
Poloniex	94.69	264.09	18.49	33.32	55.53	104.34	260.68	0.00	45.13
xBTCe	106.16	246.56	19.90	40.74	70.58	131.44	281.96	24.15	40.78

Notes: This table provides descriptive statistics of estimated arbitrage bounds for each sell-side market. We compute arbitrage bounds for a CRRA utility function with risk aversion parameter $\gamma = 2$. We estimate the bounds using the spot volatility estimator of Kristensen (2010) and out-of-sample predictions of the conditional moments of the latency based on a gamma duration model. We report all values in basis points (except otherwise noted). *Security* gives the (percentage) contribution of the required number of confirmations to the median arbitrage boundary. *Uncertainty* corresponds to the (percentage) contribution of the uncertainty in latency to the median arbitrage boundary.

2.5.4 Evidence for Arbitrage Opportunities

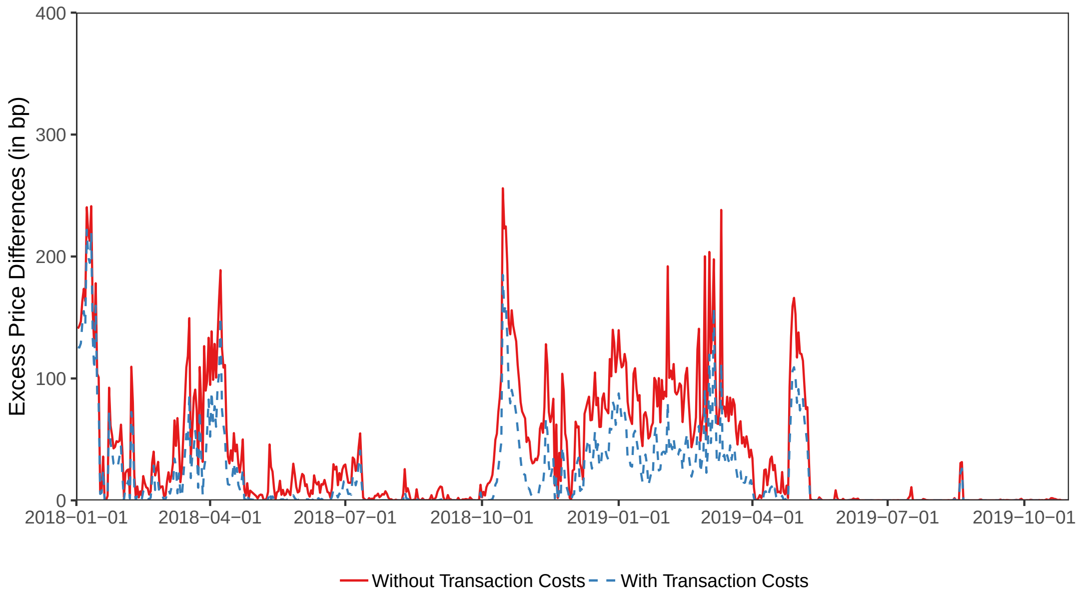
To quantify to which extent observed cross-market price differences exceed the estimated arbitrage bounds and thus constitute potential arbitrage possibilities, we define the price differences adjusted for transaction costs in excess of arbitrage bounds as

$$\tilde{\mathcal{E}}_t := \left(\tilde{\Delta}_t - \begin{pmatrix} \hat{d}_t^1 \\ \vdots \\ \hat{d}_t^N \end{pmatrix} \begin{pmatrix} 1 & \dots & 1 \end{pmatrix} \right) \odot \tilde{\Psi}_t, \tag{2.29}$$

where the (i, j)-th element of $\tilde{\Psi}_t$ is defined as $\tilde{\Psi}_{t,i,j} = \mathbb{1}\left\{\tilde{b}_t^i(q_t^{j,i}) - \tilde{a}_t^j(q_t^{j,i}) > \hat{d}_t^i\right\}$, $\mathbb{1}\{\cdot\}$ is the indicator function, and $\odot$ corresponds to the element-wise multiplication operator.

Figure 2.6 plots the time series of cross-sectional daily average price differences in excess of the arbitrage bounds. The red solid line corresponds to price differences at the best bid and best ask *not* adjusted for transaction costs. The blue dashed line shows the corresponding excess price differences after adjusting for transaction costs. Taking transaction costs into account lowers the returns in excess of arbitrage bounds on average by 25%.

Figure 2.6: Price Differences in Excess of Arbitrage Bounds over Time



Notes: This figure shows daily average minute-level returns in excess of the estimated arbitrage bounds across all exchange pairs from January 1, 2018, to October 31, 2019. The solid red line corresponds to price differences based on the best bid and best ask of the individual exchange pairs, $\mathcal{E}_t$. The dashed blue line displays the corresponding excess price differences after adjusting for transaction costs, $\tilde{\mathcal{E}}_t$.

In our sample, we find that for a coefficient of relative risk aversion equal to 2, about 84% of observed price differences fall within the estimated bounds. After adjusting for transaction costs, on average, 91% of all observed price differences are in the no-trade region. Therefore, the vast majority of cross-exchange price differences on the Bitcoin market do *not* constitute arbitrage opportunities but are still too small to be traded away by rational arbitrageurs, taking into account transaction costs and the risks due to stochastic settlement latency.

Observations outside of the arbitrage bounds might arise due to additional market frictions, which are not captured by our theory, for instance, capital controls (see, e.g., Choi et al., 2018) or exchange-specific risks. As exchanges themselves are vulnerable to different sources of risk (e.g., default or hacking risk), the disutility of being exposed to a specific exchange may prevent arbitrageurs from exploiting certain cross-market trades, unless these trades provide additional compensation outside of our current framework. Furthermore, local regulation or access restrictions may deter cross-market arbitrage activity altogether. For instance, US-based exchanges typically do not allow European citizens to open an account. To adjust for such exchange-

Figure 2.7: Excess Price Differences between Exchanges

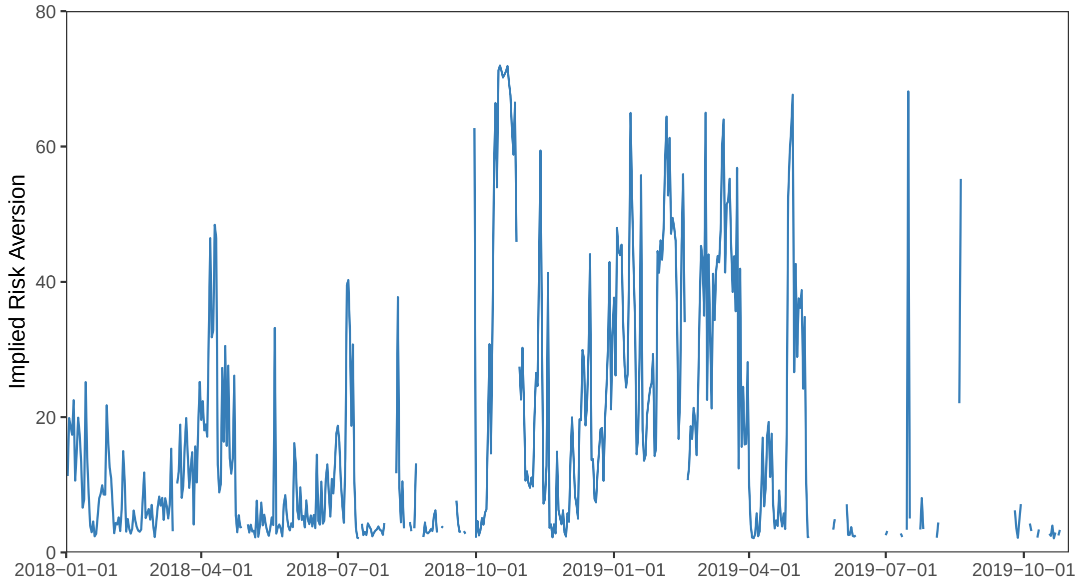
Notes: This heatmap shows the average price differences adjusted for transaction cost, $\tilde{\delta}_t^{b,s}$, in excess of the arbitrage bounds d_t^s across time for each exchange pair in our sample. Price differences are based on minute-level transaction cost-adjusted bid and ask quotes for each exchange according to Equation (2.20). We account for exchange-specific taker fees according to Table 2.1 and compute the quantity which maximizes the return for each exchange pair using a grid search algorithm. The darker the color, the larger the average price difference through our sample period in the specific exchange pair. White or very light colors indicate that there are on average no or few price differences for a specific exchange pair.

specific effects, we decompose price differences in excess of arbitrage bounds on the exchange-pair level. Figure 2.7 shows a heatmap of average excess price differences. In analogy to Figure 2.3, some exchanges in our sample seem to persistently quote lower prices than others (e.g., *Gatecoin*), even after adjusting for transaction costs and latency-implied price risk.

Observations outside of arbitrage bounds may not only occur due to additional market frictions but are also consistent with higher risk aversion. As estimates of γ in the asset pricing literature range from as little as 0.35 to as much as 9.0 (see, e.g., Hansen and Singleton, 1982; Chetty, 2006), plausible levels of relative risk aversion are hard to pin down. Therefore, in Figure 2.8, we display the *implied* relative risk aversion, $\hat{\gamma}_t$, corresponding to the lowest value of relative risk aversion which prevents all traders from exploiting the observed cross-exchange price differences.[15] We observe that the

[15]See Appendix B.5 for more details on the construction of $\hat{\gamma}_t$.

Figure 2.8: Implied Coefficient of Relative Risk Aversion over Time



Notes: This figure shows the daily average implied risk aversion parameter, $\hat{\gamma}_t$, from January 1, 2018, to October 31, 2019. We compute $\hat{\gamma}_t$ as the smallest relative risk aversion such that all observed price differences adjusted for transaction costs fall within the implied limits to arbitrage.

implied minimum risk aversion exhibits substantial variation over time with an average of around 17. This relatively high level indicates that risk aversion cannot be the only reason for observing large cross-exchange price differences but suggests the presence of further market frictions.

2.6 Arbitrage Bounds and Cross-Exchange Activity

The preceding analysis demonstrates that our derived arbitrage bounds can reconcile a large fraction of the observed cross-exchange price differences in our sample. However, these results neither provide an indication to which extent the variation in these price differences can be attributed to variation in the economic frictions underlying the arbitrage bounds nor whether arbitrageurs in fact act according to our proposed theoretical framework. Our model exhibits two key features that we should observe in the data. On the one hand, large price differences should be consistent with times of high volatility, long settlement latencies, and high uncertainty in latencies. On the other hand, during periods of large price differences, that is, in periods where price differences likely exceed the arbitrage bounds transfers of assets between exchanges should increase consistent with the notion that arbitrageurs have to physically transfer assets between markets to exploit arbitrage opportunities.

To address the relation between price differences and arbitrage bounds, we compute the cross-sectional hourly average of differences between the price level on each sell-side exchange and prices on all other exchanges. We then relate this aggregate hourly measure of price differences to hourly averages of arbitrage bounds or, alternatively, measures of their components (i.e., spot volatility and moments of the realized settlement latency distribution) as well as exchange-specific characteristics.

More specifically, we estimate the model

$$\delta_t^s = \alpha^s + \beta_1 d_t^s + \gamma_1 x_t^s + \varepsilon_t^s, \tag{2.30}$$

where s indexes all sell-side exchanges, δ_t^s are exchange s-specific average price differences in hour t, α^s is a sell-side exchange fixed effect to control for unobserved heterogeneity at the exchange level, and ε_t^s is a white noise error term. d_t^s refers to the average estimated arbitrage bound of exchange s or, alternatively, a collection of their individual components.[16] The latter includes the average hourly sell-side spot volatility, the hourly median and variance of realized waiting times of transactions entering the mempool until being included in a block for the first time (where we rescale the variance to have a mean of zero and a standard deviation of one). Finally, x_t^s contains the average hourly bid-ask spread as a measure of liquidity.

Table 2.5 provides the estimation results. Consistent with our theoretical framework, we find a statistically significant positive relation between price differences and arbitrage bounds. The marginal effect of arbitrage bounds is statistically and economically significant: a 1 bp increase in arbitrage bounds is on average associated with a 0.3 bp increase of price differences. Directly replacing the (pre-estimated) arbitrage bounds with their components confirms that large price differences are consistent with periods of high price risk due to settlement latency. Moreover, we interact the arbitrage bounds with sell-side exchange-specific dummies indicating whether the exchange offers margin trading instruments (*Margin*) and access for institutional traders (*Business Accounts*). We find that exchanges with margin trading are less sensitive to arbitrage bounds but still exhibit a significant relation between price differences and arbitrage bounds. The costs of margin trading for investors thus seem to exceed the risk-adjusted latency-implied price risk, presumably due to substantial margin re-

[16] In the latter case, d_t^s and β_1 are corresponding vectors.

quirements by the exchanges as the absence of central clearing requires costly insurance against counterparty risk. Similarly, exchanges which feature access for institutional traders are less sensitive to arbitrage bounds, consistent with the notion that large institutions are more likely to hold inventories at different marketplaces and may exploit price differences without transferring assets.

However, the sensitivity of price differences to latency-related variables on top of the presence of short-selling instruments and inventory holdings suggests that circumventing the blockchain consensus protocol via alternative strategies is not sufficiently pervasive to offset the impact of arbitrage bounds. Finally, in line with Roll et al. (2007), we also find that liquidity, measured by the magnitude of bid-ask spreads, is an additional market friction that increases cross-market price differences. The panel regression thus indicates that arbitrage bounds due to settlement latency explain price differences even after adjusting for frictions related to trading costs.

To analyze the relation between price differences and arbitrage activity, we expand our data by cross-exchange asset flows. Since exchanges are reluctant to provide the identity of their customers, it is virtually impossible to identify actual transactions by arbitrageurs. However, we take the overall transfer of assets between two different exchanges as a measure for the trading activity of cross-market arbitrageurs. For each exchange, we thus collected a list of addresses that are likely under the control of the exchanges in our sample.[17] Bitcoin transactions are pseudonymous in the sense that each transaction publicly reveals all addresses associated with the transaction, but it is hard to map these addresses to their respective physical or legal owners. Exchanges typically control a large number of addresses to keep track of individual users' assets. However, algorithms are available which link addresses to certain exchanges (e.g., Meiklejohn et al., 2013; Foley et al., 2019). Usually, the matching procedure is based on either having observed an address being advertised to belong to an exchange or by actively sending small amounts of Bitcoin to exchanges. We gathered 62.6 million unique exchange addresses which allow us to identify 3.9 million cross-exchange transactions with an average daily volume of 72 million USD in our sample period.[18] For any given hour and exchange, arbitrage opportunities involving a particular exchange might arise using the exchange as a sell-side and buy-side market during that time period. To be able to adjust for exchange-specific characteristics, we take the sum

[17] We thank Sergey Ivliev for his tremendous support on this front.

[18] We compute the average daily volume by extracting the hourly sum of net flows (inflows to an exchange minus the outflows in BTC) and multiplying it by the hourly average midquote across all exchanges.

Table 2.5: Price Differences and Sources of Price Risk

Dependent Variable:	Price Differences			
	(1)	(2)	(3)	(4)
Arbitrage Bound (in %)	0.307***		0.440***	0.442***
	(15.98)		(18.62)	(12.84)
Spot Volatility (in %)		5.416***		
		(16.99)		
Latency Median (in Minutes)		0.003***		
		(3.92)		
Latency Variance (Standardized)		0.078***		
		(3.53)		
Arbitrage Bound × Margin Trading			-0.258***	
			(-7.07)	
Arbitrage Bound × Business Accounts				-0.220***
				(-5.38)
Spread (in %)	0.111***	0.075*	0.093**	0.101***
	(2.91)	(1.95)	(2.42)	(2.65)
Exchange Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.162	0.163	0.162	0.162
Exchange-Hour Observations	213,984	213,984	213,984	213,984

Notes: This table provides OLS estimates based on a regression of hourly average sell-side exchange-specific price differences and the main components of price risk due to stochastic settlement latency. *Price Differences* is the sell-side exchange-specific average hourly price difference from all other exchanges (in percent). *Spot Volatility* is the average hourly sell-side spot volatility estimate based on one-sided Gaussian kernel estimates (Kristensen, 2010). *Latency* denotes the hourly median (variance) of the waiting time of transactions entering the Bitcoin mempool, where we rescale the variance to have a mean of zero and a standard deviation of one. *Arbitrage Bound* corresponds to the average hourly sell-side exchange calibrated arbitrage bound as of Equation (2.26). *Margin* is a dummy variable that indicates the availability of margin trading instruments, and *Business Accounts* indicates whether exchanges offer access for institutional investors. We compute *Spread* as the hourly sell-side exchange-specific average percentage spread. We report t-statistics based on heteroskedasticity-robust standard errors in parentheses. ***,**, and * indicate statistical significance on the $1\%, 5\%$ and 10% levels (two-tailed), respectively.

of cross-market flows *into* exchange s in hour t and denote the resulting aggregated variable as f_t^s.

In addition, we have to take into account that cross-market asset flows, f_t^s, and price differences, δ_t^s, are jointly determined, giving rise to a simultaneity problem. On the one hand, arbitrage activity is expected to increase with higher price differences (in excess of arbitrage bounds). On the other hand, price differences should decrease in response to arbitrage trades as arbitrageurs enforce adjustments towards the law of one price. To overcome the resulting inconsistency of estimates in a regression of f_t^s on δ_t^s, we use the estimated arbitrage bounds and, alternatively, their components as instruments for price differences. Arbitrage bounds satisfy the two necessary conditions for the validity as an instrument. First, we find a positive correlation between price differences and arbitrage bounds after netting out the effects of other exogenous variables (see Table 2.5). Second, the only role arbitrage bounds play in influencing cross-market flows is through their effect on the endogenous price differences.

We hence estimate the model

$$f_t^s = \beta_2 \hat{\delta}_t^s + \gamma_2 x_t^s + \varepsilon_t^s, \tag{2.31}$$

by two-stage least squares, where $\hat{\delta}_t^s = \hat{\alpha}^s + \hat{\beta}_1 d_t^s + \hat{\gamma}_1 x_t^s$ denotes the fitted values obtained from the regression in Equation (2.30) and x_t^s corresponds to the exchange-specific spread to control for liquidity.

Table 2.6 reports the results of the two-step estimation procedure. The first two columns take the US Dollar value of flows as the left-hand-side variable, while the last two columns take their natural logarithm to reduce the impact of outliers. In columns (2) and (4), we use the estimated arbitrage bounds as instruments, while in columns (1) and (3) their components (spot volatility, median settlement latency and variance of realized latencies) serve as instruments.

Throughout all specifications, we find a significant positive relation between cross-exchange flows into an exchange and (instrumented) price differences: a one-percentage-point increase in price differences is on average associated with a 0.5% increase in asset flows into an exchange in a given hour. These results are robust to controlling for bid-ask spreads, which are negatively related to inflows coming from other exchanges. The negative marginal effect of the bid-ask spread is consistent with the notion that higher transaction costs deter arbitrageurs' activity. Hence, the regression results indicate that cross-exchange flows increase in response to larger price differences triggered by larger arbitrage bounds. This provides evidence for arbitrageurs chasing profitable arbitrage opportunities by actively transferring assets across markets.

2.7 Conclusion

Many market participants believe that distributed ledger technology has the potential to radically transform the transfer of assets. Replacing trusted intermediaries and central clearing parties with decentralized consensus protocols may increase efficiency and security. However, a new friction emerges as the potential merits come at the cost

Table 2.6: Cross-Exchange Flows and Arbitrage Opportunities

Dependent Variable:	Exchange Inflows (in 100k USD)		Log(1 + Exchange Inflows)	
	(1)	(2)	(3)	(4)
Price Differences (in %)	2.407***	2.525***	0.468***	0.462***
	(17.03)	(15.09)	(17.63)	(15.53)
Spread (in %)	-0.355***	-0.376***	-0.068***	-0.066***
	(-3.74)	(-3.73)	(-3.67)	(-3.61)
Exchange Fixed Effects	Yes	Yes	Yes	Yes
Exchange-Hour Observations	213,984	213,984	213,984	213,984

Notes: This table provides the estimated marginal effects based on a two-stage least square regression of cross-exchange asset flows on price differences and bid-ask spreads. *Inflows* are the average hourly BTC inflows (in USD) to market s from all other markets in our sample. *Price Differences* are the fitted values of Equation (2.30) and denote price differences on sell-side market s. In columns (1) and (3), we instrument price differences with all components of arbitrage bounds. Columns (2) and (4) correspond to the estimation results where we directly use the estimated arbitrage bounds as an instrument. We compute *Spread* as the hourly sell-side exchange-specific average percentage spread. We report t-statistics based on heteroskedasticity-robust standard errors in parentheses. ***,**, and * indicate statistical significance at the $1\%, 5\%$ and 10% levels (two-tailed), respectively.

of latency in the settlement process. We theoretically show that settlement latency implies limits to arbitrage as it exposes arbitrageurs to price risk. We derive arbitrage bounds for arbitrary concave utility functions and a general class of latency distributions. The arbitrage bounds increase with spot volatility, risk aversion, expected latency, and uncertainty in latency. Furthermore, we calibrate these arbitrage bounds for the special case of a utility function with constant relative risk aversion.

We quantify limits to arbitrage in the Bitcoin market and find that settlement latency is a quantitatively important market friction which imposes arbitrage bounds of, on average, 121 bp. The quantification of latency-induced limits to arbitrage is essential to assess the efficiency of a market relying on distributed ledger technology. In fact, we show that on average, 91% of observed Bitcoin price differences adjusted for transaction costs are within the corresponding arbitrage bounds.

We also provide direct evidence for the economic impact of settlement latency. The law of one price is substantially violated and price differences are particularly large during times of high latency-implied price risk. We also collected a novel data set of exchange wallets to examine cross-exchange Bitcoin flows and find that asset transfers between exchanges respond to price differences adjusted for latency-implied price risk. The findings provide direct evidence that price differences are actively explored by risk-averse arbitrageurs only if potential gains offset latency-implied price risk.

Therefore, our analysis illustrates that trustless markets come at substantial costs with potentially far-reaching implications. First, limits to arbitrage implied by settlement latency may harm price efficiency, as the lower activity of arbitrageurs reduces the information flow across markets. Second, deviations from the law of one price affect the pricing of securities, as risk neutral probabilities are not uniquely defined. Third, the implied costs of settlement latency depend on the design of the distributed ledgers and should influence the decision whether to migrate to a decentralized settlement system. Overall, our paper provides an initial step to understand the impact of decentralized settlement on financial markets.

2.8 Acknowledgments

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3 Perceived Precautionary Savings Motives: Evidence from FinTech

Joint work with Francesco D'Acunto, Thomas Rauter, and Michael Weber

We study the spending response of first-time borrowers to an overdraft facility and elicit their preferences, beliefs, and motives through a FinTech application. Users increase their spending permanently, lower their savings rate, and reallocate spending from non-discretionary to discretionary goods. Interestingly, liquid users react *more* than others but do not tap into negative deposits. The credit line acts as a form of insurance. These results are not fully consistent with models of financial constraints, buffer stock models, or present-bias preferences. We label this channel *perceived* precautionary savings motives: liquid users behave as if they faced strong precautionary savings motives even though no observables, including elicited preferences and beliefs, suggest they should.

3.1 Introduction

During recessions, monetary and fiscal policies aim to stimulate consumption through credit because household consumption comprises the largest share of gross domestic product (Agarwal et al., 2017). At the same time, household credit growth has been a major and often unforeseen driver of financial crises (Schularick and Taylor, 2012; Baron and Xiong, 2017; Di Maggio and Kermani, 2017; Mian and Sufi, 2015; Mian et al., 2017). Understanding the micro-level channels through which household credit affects consumption and saving decisions is thus important to understand the dynamics of business cycles and to inform the design of effective credit-based expansionary policies.

In this paper, we introduce a unique FinTech setting in which we observe the extensive margin of credit—initiation of overdraft facilities to first-time borrowers—

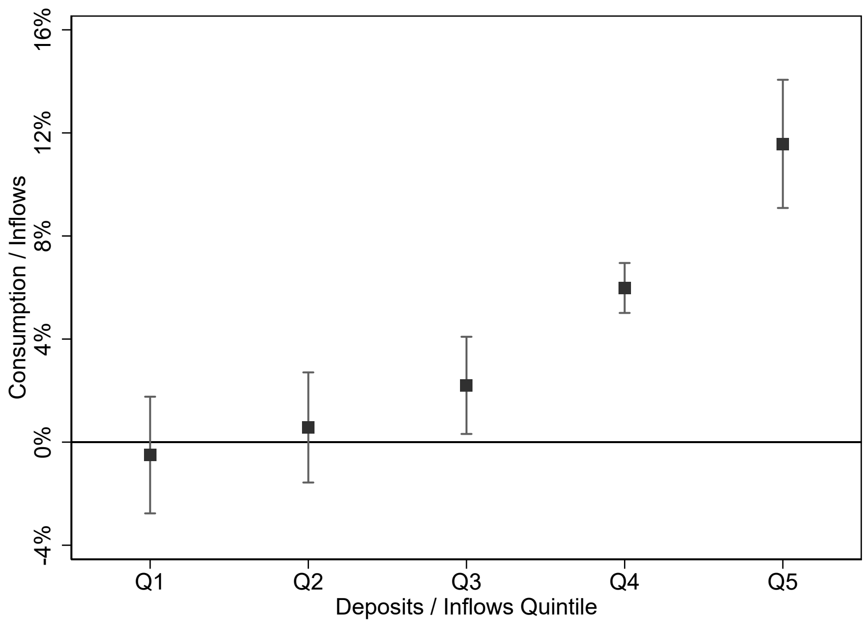
combined with the possibility to elicit *directly* a set of preferences, beliefs, and individual perceptions that theoretical and empirical research commonly relates to households' saving and consumption behavior. These dimensions, which are typically unobserved in large-scale micro data, include risk preferences, patience, expectations about future employment status, future large expenses, medical expenses, bequest motives, subjective life expectancy as well as financial literacy and generalized trust in others. We use this setting to estimate the consumption effects of providing first-time borrowers with a credit facility and to test directly for a broad set of typically unobserved channels that, based on earlier theoretical and empirical research, might explain the effects of credit on spending.

In our baseline analysis, we estimate a set of double-differences specifications in which we compare bank users' change in consumption spending after activating the overdraft facility relative to before and relative to users whose overdraft facilities are not yet activated. The average user increases her spending by 4.5 percentage points of income inflows after credit is available relative to before and relative to users whose overdraft facility is not yet active. This positive effect on spending does not revert fully over time—we detect permanent increases in spending and drops in savings for the average user.

The surprising result is that the baseline effect is heterogeneous across users but not based on dimensions earlier research proposed, such as motives to smooth consumption or liquidity constraints. Instead, Figure 3.1 shows that the effect increases monotonically as the liquidity of users increases. The higher the ratio of liquid deposits to income inflows, the stronger is the spending reaction to the provision of credit. Moreover, the higher this ratio, the more permanent is the effect as we document below.

Liquid users seem to behave as if they have strong precautionary savings motives and hence accumulate liquid savings before the overdraft facility is available. They have inflows over the previous twelve months similar to other users but save a larger fraction of their income by spending substantially less. Once the overdraft becomes available, consistent with an insurance effect of the facility, liquid users start spending more of their existing liquid savings and decrease their savings rate permanently. Interestingly, liquid users do *not* use the overdraft facility, in the sense that only 10% of them ever tap into negative deposits and make use of the credit line. The availability of an overdraft facility makes these users dissave part of their existing liquidity but not more than that, again consistent with strong precautionary savings motives that are reduced once the facility is available.

Figure 3.1: Consumption Response by Deposit-to-Income



Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft. To generate the plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles of deposits to inflows from lowest to highest. We then interact the resulting grouping variable with a binary indicator that equals 1 if a user has access to a mobile overdraft in a given month. Vertical bands represent 95% confidence intervals for the point estimates in each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

The spending response by liquidity is a robust feature of the data. First, we rule out that our results are driven by the amount or volatility of inflows into the account before the credit line is available. Moreover, the results are similar if we only consider individuals who consume large parts of their inflows, for alternative definitions of deposits to inflows, for users in areas that have high versus low savings rates—and hence potentially different social norms about the importance of savings—for urban versus rural users, or users living in former communist countries and others. Thus, peculiar norms of saving or aversion to debt in specific European countries, such as Germany, do not drive our results.[1]

Our results are puzzling to the extent that the previous literature typically found that liquidity constraints drive borrowers' reaction to the credit availability. Hence, the least liquid users should react the most in terms of spending—the opposite of our

[1]We thank Amit Seru for suggesting sample splits based on areas with different norms about saving and borrowing within and across European countries.

finding. For instance, research that studies increases in the intensive margin of credit, such as increasing existing credit card limits, finds that users at the constraint (i.e., that maxed out their previous limit) react more to the increase of credit lines (see, e.g., Gross and Souleles, 2002; Aydin, 2015; Agarwal et al., 2017). The crucial difference of our setting is that we study the provision of credit lines to borrowers who did not have access to credit beforehand (extensive margin of credit).[2] The insurance role of obtaining a credit facility for the first time does not apply to borrowers who already had access to credit, and hence the effect we document could not arise in earlier settings that vary the intensive margin of credit. Another difference between our results and earlier research is that our liquid users do not tap into negative deposits but only consume out of their existing savings and new inflows, which suggests that changes in credit limits or in the intensive margin of credit would barely have any effect on them.

To understand whether standard determinants of precautionary savings motives explain our results, we exploit the fact that our FinTech provider allows us to reach users directly through their app and elicit their preferences, beliefs, and motives. First, risk aversion and/or prudence are important potential drivers of savings behavior independent of income volatility (Gomes and Michaelides, 2005). We detect no economic or statistical differences in the levels of risk aversion and patience across users based on their liquidity. Moreover, users who have high subjective beliefs about future large expenses, such as medical expenses, or about future income uncertainty (Guiso et al., 1992; Ben-David et al., 2018) might save a larger fraction of their income. Even here, we find no systematic differences in the cross-section of deposit to inflows. We do not find systematic differences in terms of subjective life expectancy, beliefs about future employment status, health conditions, or bequest motives, either. Finally, we do not find any systematic differences in terms of financial literacy or generalized trust—liquid users understand the incentives to borrow and save similarly to other users.

Ultimately, the majority of users—all those above the bottom 40% by liquidity—behave as if they had precautionary savings motives before accessing the credit line. These motives disappeared with the activation of credit lines, which we could interpret as a form of insurance against future negative states. At the same time, none of the standard explanations for precautionary savings motives appear to have the potential to explain our results, either individually or jointly. For this reason, we label our mechanism "perceived precautionary savings"—users perceive strong precautionary

[2]We discuss the institutional setting in detail in Section 2.

savings motives, but neither their preferences, subjective or objective beliefs or other characteristics we elicit directly based on earlier theoretical and empirical research, explain these motives.

We argue that neither models of buffer stock consumption (Deaton, 1991; Carroll, 1997), buffer stock consumption with durables (Guerrieri and Lorenzoni, 2017; Aydin, 2015), the standard life-cycle permanent income model of Friedman (1957) nor heterogeneous-agents models with assets of different liquidity (Kaplan et al., 2014) can explain our results in full. Non-standard preferences such as present-biased preferences are also unlikely to explain all our results. If the users who react the most to overdraft activation were present-biased, they would have consumed out of their higher deposits even *before* activating the overdraft facility, which is not true in the data. Our results are closer to Olafsson and Pagel (2018) who document that FinTech app users who hold wealth in deposit accounts and use overdraft facilities at the same time increase consumption spending on paydays. In our setting, we show that individuals with the highest deposits-to-inflows ratio react the most in terms of spending once they activate the overdraft facility, whereas in Olafsson and Pagel (2018) individuals with lower amounts of deposits spend more in response to income payments. Ultimately, our results call for further theoretical and empirical evidence on potential alternative drivers of precautionary savings motives, either based on standard or non-standard beliefs. For instance, a promising direction could be to allow heterogeneity in the extent to which agents have biased beliefs regarding the occurrence of small-probability events, such as catastrophic states of the world.

A remaining concern with our baseline double-differences analysis is that users might activate the overdraft facility endogenously when they know they are about to make a large expense. The facts that the spending effect for liquid households is permanent and that elicited expectations about upcoming large expenses do not differ across liquid and illiquid users reduce this concern.

To address this concern directly, we propose two tests. First, we repeat our double-differences analysis restricting the sample only to users who activated their overdraft facility in the first month in which the bank made it available.[3] The rationale is that the timing at which the bank decided to make the facility available can barely coincide with the timing at which users would have endogenously decided to activate the facility because users did not know that the overdraft facility would have been made available at that time. Although the sample size drops substantially in this test, we esti-

[3]We thank Greg Buchak and Michaela Pagel for suggesting this test.

mate the same monotonic pattern in terms of change in spending by liquidity quintiles and we can reject the null hypothesis that the changes are zero at conventional levels of significance for the top two quintiles.

For the second test, we propose a sharp regression discontinuity design (RDD) that exploits the rule the FinTech provider uses to compute the limit of the overdraft facility. This limit is a rounded function of users' income based on a set of pre-specified income bandwidths of which users are not aware. The FinTech application computes the limits automatically, with no role for bank officers to change the approved limits—this is why the app allows users to open the approved line of credit automatically in just a few seconds—and hence there is no scope for manipulating one's assignment to the high- or low-treatment group.

In this RDD, we compare users that are observationally indistinguishable, as we document directly, but end up being assigned different overdraft limits based on small differences in their income inflows. This assignment combines the extensive margin of credit—so that the insurance effect of the facility exists for everybody—with a higher or lower intensive margin in terms of credit limit. The RDD confirms the consumption response to the availability of credit. We cannot use this RDD for our baseline analysis and heterogeneity tests because by construction the RDD only uses a small subset of users who are close to the sharp threshold. Heterogeneity in the RDD sample is minimal by construction given that the treated and control users are almost identical in most characteristics.

Ultimately, our results might provide novel insights into the effects of providing credit to households over the business cycle. Providing insurance against potential negative future spending shocks appears to increase the spending of households with high deposit-to-inflows ratios. However, this policy intervention would not increase their debt positions or interest payments because these users would not draw on the overdraft facilities. If anything, providing insurance to these households at times of economic slumps might increase aggregate demand swiftly since households that hoard cash due to perceived precautionary savings motives might end up spending parts of their savings. Also, providing insurance to perceived precautionary savers might be virtually costless based on our results because these individuals would not end up paying any interest and would not accumulate debt over time.

The main challenge to policies based on our findings might be political in nature. During times of economic crisis, policy-makers would provide virtually costless insurance to *wealthier* households (in terms of liquid wealth) to nudge them to spend more instead of providing subsidies to induce spending by all households, including those who might become risky borrowers over time. Whether governments might find enough political support for this type of policy is a matter for future research in political economy and political sciences.

Methodologically, the paper suggests a compelling reason for macroeconomists and financial economists to use FinTech settings for research on household borrowing, saving, and spending. FinTech platforms allow the researcher to access users directly in a logistically simple way that barely involves any costs because users can be contacted interactively through apps. Easy direct access to users allows the elicitation of typically unobserved characteristics, as demonstrated in this paper, and has potential for field experiments to gauge the causal effects of theoretical channels that act through preferences, beliefs, and perceptions on actual high-stake decision-making.

3.2 Institutional Setting

We cooperated with a leading European FinTech bank to test for the effects of introducing a mobile overdraft facility on consumption spending. The digital-only bank does not operate a branch network and provides all its services through an Android or iOS mobile app. The bank currently operates under a European banking license in several countries and has more than 1 million customers.

Users can open a bank account within 10 minutes by entering their personal information into the app. They are required to verify their identity by providing a copy of their passport or personal identification through video conferencing before the bank confirms the account and users obtain their debit card by mail. The free mobile checking account is the bank's baseline product. Contrary to US banks, our FinTech lender does not offer credit cards, which is common in the countries in which it operates. Moreover, note that EU legislation does *not* require banks to provide any credit facilities to their customers, which is why our setting allows us to test for the effects of providing an overdraft facility to users for the first time that allows borrowing for consumption spending.[4]

In terms of day-to-day operations, customers manage their account entirely via the bank's mobile app, which provides monthly consumption statistics and allows users

[4]For instance, for the case of Germany, the largest European country, which enters our sample, see the information sheet by the national bank regulator, BaFin: https://www.bafin.de/DE/Verbraucher/Bank/Produkte/Dispokredit/dispokredit_node.html.

to set their daily payment and withdrawal limits, lock their card, or change their PIN in real time.

In February 2015, the bank started to offer a mobile credit line to users across several European countries. Residents of these countries with a sufficiently high credit score are eligible for the mobile overdraft facility. Customers can activate the credit line directly in their mobile app within one minute and receive a maximum overdraft amount that ranges between 500 and 5,000 Euros depending on their credit score and other financial and personal characteristics. The bank uses a fully automated algorithm to allocate maximum credit amounts to users. In Section 3.6, we describe the bank's loan granting and credit allocation process in detail. Users who are granted a mobile credit line specify their desired credit amount which they can change in real time via the mobile app depending on their consumption needs. However, customers cannot select an amount that exceeds the maximum overdraft limit granted to them by the bank. Users pay an annual interest rate of approximately 10 percentage points on their used overdraft amount, which the bank charges once per quarter. The mobile app provides daily updated information on users' accrued interest costs. Customers can turn on push notifications that remind them whenever their account balance turns negative and they start using the overdraft. The bank cancels the mobile credit line if users default on their interest payments, receive unemployment benefits, or experience direct debit reversals.

3.3 Data and Descriptive Statistics

3.3.1 Data Sources and Sample Selection

Our sample consists of users who received an overdraft between February 2015 and September 2017. We focus on individuals that the bank classifies as main account users based on their consumption and inflow history to alleviate the concern that customers might have additional accounts with other banks, which we cannot observe directly. Main account users are individuals that receive a regular monthly salary or incoming standing order into their mobile checking account for at least two consecutive months. Prior research shows that European bank clients satisfy approximately 70% of their daily consumption needs through their primary salary account and that the majority of individuals only has one bank account (Bain, 2017; ING, 2018). As a result, our consumption and overdraft data cover most if not all financial activities that main account users carry out via their mobile bank account. In a set of robustness analysis, we show that our results do not change if we use other thresholds or alternative filters to screen out users who are unlikely to be main account users.

For all the users in our sample, we first obtained detailed transaction-level consumption data, credit line information, and personal user characteristics from the bank. Specifically, we received information about the type, amount, and timestamp of all financial transactions that pass through users' checking accounts between February 2015 and March 2019. To protect users' identity, the bank rounded all transaction amounts to the nearest Euro and only provided us with the day but not the exact time of each transaction. Our raw dataset contains 58,310,004 individual financial transactions, which we aggregate into user-month observations. Each within-user time series starts with the month in which the user signed up on the mobile app, verified her identify, and the bank opened the account, and ends with the closing of the account or the last month of our sample period (March 2019). We code observations of our flow variables as zero if the user did not have any corresponding financial transaction in the given month.

An important feature of the transaction-level data is the classification of financial transactions into categories, which the bank provided to us. The first classification consists of six broad categories based on the transaction method: (i) cash deposits and withdrawals, (ii) incoming or outgoing wire transfers within the Single Euro Payments Area (SEPA), (iii) foreign wire transfers from or to non-SEPA countries, (iv) direct debit withdrawals (including reversals), (v) bank-imposed fees, and (vi) card-based electronic payments. In a second classification, which captures the scope of each transaction, the bank categorizes each debit-card payment into one of seventeen merchant category code (MCC) groups, based on the vendor that receives the payment. MCC groups specify the vendor's industry and allow us to identify which type of product or service the account holder purchased. The seventeen MCC groups cover a broad range of users' consumption spending and include both discretionary (e.g., entertainment, shopping, or gastronomy) and non-discretionary consumption categories (e.g., groceries, family, or utilities/furniture).

In addition to the transaction-level data, we obtained data on the activation and usage of credit lines. This dataset contains granular information about the application date, the granted overdraft amount, and activating users' financial characteristics. We observe all user-specific input parameters that enter the bank's credit allocation algorithm, including each individual's credit score, employment status, regular salary, and other credit-relevant inflows.

Since the bank shared the precise inner workings of its overdraft granting process with us, we are able to perfectly replicate the credit allocation decision for all mobile credit line users in our sample. Moreover, the credit-line dataset contains the complete history of all overdraft setting changes that users made once the credit facility was activated.

Finally, the bank provided us with additional data on the demographic and personal information of each main account user. We obtained data on users' gender, year of birth, and residential zip code. To ensure data anonymity, the bank did not share the name, address, or precise date of birth of account holders.

3.3.2 Descriptive Statistics

Table 3.1 provides descriptive statistics for our main overdraft sample. We define all the variables we use in the empirical analysis in Appendix Table C.1. We trim all ratios that involve consumption-related variables at the 5^{th} and 95^{th} percentile to mitigate the impact of outliers due to data errors or extreme values.[5]

Our final dataset contains 603,157 user-month observations for 36,005 unique individuals who obtained a mobile credit line between February 2015 and September 2017. As is common in FinTech settings,[6] the user base of the bank consists primarily of male millennials who live in urban areas. The average user in our sample is 34 years old, has monthly inflows of 2,220 Euros, and opened the mobile bank account 1.6 years ago. Female users represent about one fifth (21%) of the sample, and about half of the users live in large cities with more than 500,000 inhabitants (53%).

In terms of spending, all overdraft users combined spent a total of 441 million Euros via their mobile checking account over our sample period. On average, these individuals consumed 48% of their monthly inflows, of which approximately two thirds are attributable to electronic card transactions and the remainder is cash consumption. For each Euro that users spent electronically on non-discretionary goods, they purchased 61 cents of discretionary items. Main account users had access to the bank's mobile overdraft facility in 91% of all user-months. The average maximum overdraft amount

[5]We obtain similar results when we instead winsorize our regression variables at the 5^{th} and 95^{th} percentile or when we use alternative trimming approaches (e.g., trimming at the 1% level in each tail).

[6]For instance, see D'Acunto et al. (2019), Gargano and Rossi (2018), D'Acunto et al. (2019), and D'Acunto and Rossi (2020).

Table 3.1: Descriptive Statistics

	N	Mean	SD	P10	P25	P50	P75	P90
User Age [Years]	603,157	34.07	9.93	23.91	27.00	31.49	38.66	48.91
Female [0/1=Yes]	603,157	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Urban [0/1=Yes]	603,157	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Account Age [Years]	603,157	1.57	0.86	0.47	0.88	1.49	2.18	2.78
Overdraft Available [0/1=Yes]	603,157	0.91	0.29	1.00	1.00	1.00	1.00	1.00
Overdraft Amount [Euro]	574,328	1,561.38	1,602.05	500.00	500.00	1,000.00	2,000.00	3,000.00
Consumption [Euro]	603,157	730.81	949.42	0.00	131.00	465.00	993.00	1,715.00
Inflows [Euro]	603,157	2,219.84	5,948.55	90.00	380.00	1,124.00	2,534.00	4,564.00
Consumption / Inflows [%]	603,157	48.11	44.89	0.00	13.88	37.24	70.08	108.00
Card Consumption [Euro]	603,157	498.58	736.64	0.00	67.00	281.00	646.00	1,206.00
Card Consumption / Inflows [%]	603,157	33.80	37.17	0.00	6.49	22.12	47.85	84.72
Cash Withdrawals [Euro]	603,157	220.92	400.55	0.00	0.00	90.00	300.00	600.00
Cash Withdrawals / Inflows [%]	603,157	13.44	19.56	0.00	0.00	5.33	19.27	40.00
Discretionary [Euro]	603,157	208.36	419.58	0.00	1.00	70.00	242.00	550.00
Non-Discretionary [Euro]	603,157	290.22	469.75	0.00	26.00	159.00	373.00	692.00
Discretionary / Non-Discretionary [%]	484,683	61.03	79.26	0.00	7.66	34.41	82.45	155.17

Notes: This table reports descriptive statistics for our user-month panel. The sample consists of 36,005 users that received an overdraft between February 2015 and September 2017 and covers each individual's complete transaction history from February 2015 to March 2019. For each variable, we report the number of observations (N), mean, standard deviation (SD), 10% quantile (P10), 25% quantile (P25), median (P50), 75% quantile (P75), and 90% quantile (P90). We define all variables in Appendix C.1.

equals 1,561 Euros.

3.4 The Effect of Mobile Overdrafts on Users' Spending Behavior

In this section, we first assess how the average user changes her spending behavior once she activates the overdraft facility on her mobile phone. We then move on to document a set of heterogeneity results in users' response to the availability of the credit line. We find that users with higher ratios of deposits to income flows are the ones reacting the most in terms of increasing their spending after they obtain access to the overdraft facility.

Our baseline analysis considers individuals' monthly consumption expenditures and uses a double-differences (DD) design. The DD estimator compares changes in the level of spending around the activation of mobile overdrafts between individuals that already have and those that do not have access to the credit line yet. We restrict the analysis to mobile overdraft users only to address the endogeneity of being eligible for the overdraft facility, which by construction depends on a set of demographic characteristics that might be correlated with changes in spending patterns over time.

Moreover, the DD design allows us to address the concern that individuals who never activate the overdraft despite being eligible might differ systematically from active users based on unobserved characteristics. These characteristics might also predict spending patterns over time, such as users' inattention to their financial situation or the possibility that some individuals use the bank account only for the purpose of depositing their money but do not use it for regular consumption activities.

The baseline DD design does not account for the possibility that unobserved shocks at the individual level determine the *timing* of users' overdraft activation and spending patterns over time. We tackle this concern directly later in the paper in two ways. First, we repeat the analysis after restricting the sample to users who activated the overdraft facility in the first month in which the bank made it available. The concern of endogenous timing of activation is less compelling in this subsample because these users could not foresee this option well in advance before activation. Second, we propose a sharp RDD that only compares users at the time they activate their facilities, relative to before.

Despite the potential endogeneity of the timing of activation, we use the DD design for the baseline analysis because this design allows us to assess potential channels driving the consumption response in the full sample. Instead, by construction, the RDD is based on estimating local treatment effects among a restricted subsample of users in the overall population, based on their closeness to the regression discontinuity we exploit.

3.4.1 Overall Consumption Expenditure Response

For our DD analysis, we estimate the following OLS regression model:

$$\text{Consumption Spending}_{i,t} = \beta \times \text{Overdraft Available}_{i,t} + \text{Fixed Effects}_{i,t} + \varepsilon_{i,t}. \quad (3.1)$$

The dependent variable is the sum of all cash withdrawals and debit-card transactions by individual i in month t, divided by the amount of the user's account inflows in month $t-1$. Our main variable of interest, *Overdraft Available*, is an indicator variable that equals 1 if the user has access to a mobile overdraft facility in the given month.

We include user fixed effects to absorb time-invariant systematic differences in consumption spending patterns across overdraft users, such as differences in occupation, gender, cultural background, or education. We also include NUTS 3 $\times$ year-month fixed effects to account for concurrent but unrelated time-varying economic or institutional changes within local sub-national districts called NUTS 3 in the European Union, which correspond to US counties.

We draw statistical inferences based on double-clustered standard errors at the NUTS 2 region and year-month levels because consumption patterns are likely correlated cross-sectionally and over time within close-by locations. We use a broader geographic definition for the spatial clustering of standard errors because the NUTS 2 level, which corresponds roughly to the state level in the US, fully subsumes the NUTS 3 level in the EU's administrative classification. This level of clustering is more conservative than NUTS 3 because it allows for correlation of unknown form across the residuals not only across users in the same county but also across users in neighboring counties that belong to the same region. Because cross-sectional residuals of decision units are typically positively correlated across space, the NUTS 2 level of clustering is also more conservative than clustering standard errors at the individual level. We verify this claim directly by repeating our baseline estimations separately using different levels of clustering, including different geographic partitions and individual-level clustering, and indeed we find that the confidence intervals around our point estimates are wider when we cluster at the NUTS 2 level than at the individual level (see the bottom right panel of Figure 3.6).

In Table 3.2, we present the estimated effects of mobile overdraft availability on consumption behavior. Column (1) documents an average positive effect of mobile overdrafts on users' monthly consumption expenditures. In terms of magnitude, overall cash and card-based consumption normalized by the user's lagged account inflows increases by 4.572 percentage points (t-statistic: 11.11), which corresponds to an increase of approximately 9.5% relative to the pre-treatment sample mean (4.572/48.11). In columns (2) and (3), we differentiate between cash withdrawals, that is, cash spending, and debit-card spending. We find that account holders increase their spending significantly through both payment types. In relative terms, the increase in card-based spending (coefficient: 3.152; t-statistic: 9.71) is larger than the increase in cash withdrawals (coefficient: 1.345; t-statistic: 7.73) and accounts for approximately 70% of users' overall consumption response. Finally, in column (4), we study the change in the ratio between discretionary and non-discretionary spending and find that users increase their discretionary spending by 2.9% relative to their non-discretionary spending.

Apart from users' timing to activate the overdraft, we can interpret our DD esti-

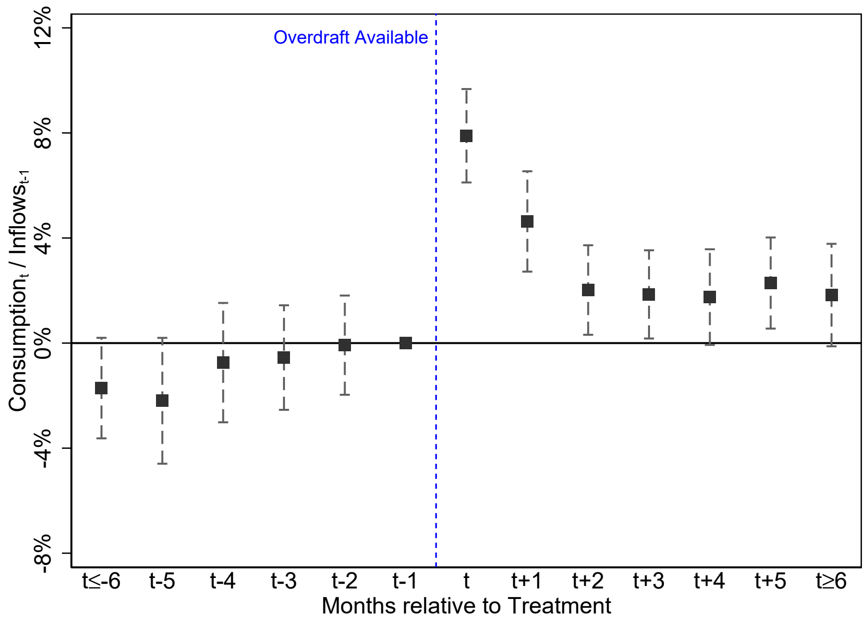
Table 3.2: Effect of Overdraft Availability on Users' Consumption Behavior

Dependent Variable (×100):	$\frac{\text{Consumption}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Card Consumption}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Cash Withdrawals}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Discretionary}_t}{\text{Non-Discretionary}_t}$
	(1)	(2)	(3)	(4)
Overdraft Available_t	4.572***	3.152***	1.345***	2.902***
	(11.11)	(9.71)	(7.73)	(5.38)
Economic Effect Size:	9.503%	9.325%	10.007%	4.755%
Fixed Effects:				
User	Yes	Yes	Yes	Yes
NUTS 3 × Year-Month	Yes	Yes	Yes	Yes
Standard Error Clusters:				
NUTS 2	48	48	48	48
Year-Month	49	49	49	50
Adjusted R^2	0.301	0.300	0.339	0.185
User-Year-Month Observations	603,157	603,157	603,157	484,683

Notes: This table provides coefficient estimates of OLS regressions estimating the effect of mobile overdraft facilities on users' consumption behavior (equation (3.1)). *Consumption* is the sum of users' *Card Consumption* and *Cash Withdrawals* in the given month. *Card Consumption* is the user's total amount of electronic card consumption. *Cash Withdrawals* is the user's total amount of cash withdrawals from ATMs in the given month. *Inflows* is the total amount of all incoming transactions a user receives in the given month. *Discretionary* is the sum of users' monthly spending on Entertainment, Shopping, Gastronomy, and Travel. *Non-Discretionary* consumption equals Card Consumption minus Discretionary spending. *Overdraft Available* is a binary indicator that equals 1 if the user has access to a mobile overdraft in the given month. We compute the *Economic Effect Size* as the pre-treatment average of each outcome variable multiplied by the corresponding coefficient estimate. We report t-statistics based on standard errors double-clustered at the NUTS 2 and year-month level in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

mates causally only subject to the assumption that the spending behavior of treated and control users would have followed parallel trends in the absence of the activation of the credit line. This parallel-trends assumption is not testable, but we can directly assess whether the spending behavior of treated and control users followed parallel trends before the shock. In Figure 3.2, we provide graphical evidence that treated and control users have parallel and almost identical consumption patterns during the time period leading up to the mobile overdraft activation. Treated users sharply increase their spending during the first two months in which they have access to the credit line. Subsequently, the treatment effect stabilizes at around 2% higher consumption relative to inflows and does not fully revert in the long run. We can reject the null hypothesis of no differences between the spending of treated and control users throughout the sample period and at any horizons we observe in the data after activation. As we discuss below, these baseline effects mask substantial heterogeneity—some groups of users face a permanent spending effect of the overdraft facility, whereas the effect dissipates

Figure 3.2: Consumption Pattern around Overdraft Availability



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of mobile overdrafts on users' consumption behavior. We estimate model (1) from Table 3.2 but replace the *Overdraft Available* indicator with separate time dummies, each marking a one-month period (except for event period $t-1$).

over time for other users.

3.5 Heterogeneity and Perceived Precautionary Savings

Our results so far have focused on average effects across users. To investigate the economic channels behind the baseline results and to assess the extent to which existing models might explain them, we study the heterogeneity of the baseline consumption effect in the cross-section of users (Jappelli and Pistaferri, 2017).

The observational data we have do not include direct information on a set of characteristics that are crucial to assess the relevance of different models, such as risk aversion, bequest motives, and beliefs. This lack of information typically makes it hard for empirical studies to pin down channels. To solve this problem, we exploit the unique feature that our FinTech bank can communicate with users through the online app to elicit preferences and beliefs *directly* through a survey instrument. This elicitation is a methodological contribution of our paper and the main reason for why the FinTech nature of the lender with which we cooperate is central to our analysis. Without the FinTech app interface, accessing traditional bank users to elicit characteristics directly would require either inviting these individuals to a human-subjects laboratory or sending surveys via mail or phone call, which would limit substantially the scope and possibility of the intervention. We see our paper as one of the very first papers that emphasize the potential for using app-based online bank settings to elicit characteristics of borrowers that would otherwise be barely observable in most real-time studies of borrowing and spending.

3.5.1 Consumption Smoothing? Income Growth and Age

We start by assessing the heterogeneity of the baseline effect across two characteristics we can observe in the field data, that is, (i) the growth of income inflows 6 months after overdraft activation relative to 6 months before activation, and (ii) users' age.

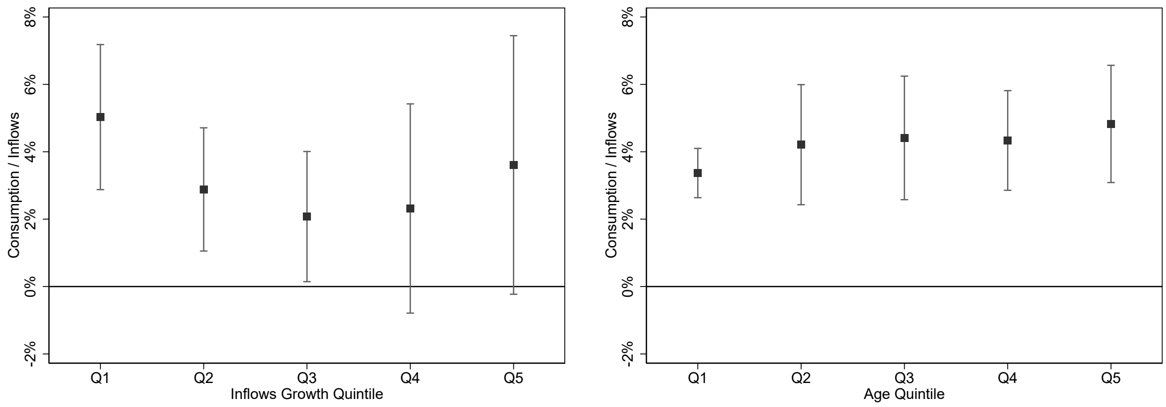
The permanent income hypothesis (PIH) suggests that agents want to smooth their consumption over time. Empirically, income paths are increasing early in life before flattening out. Hence, the PIH predicts that younger users and users with a steeply increasing income path are more likely to use the overdraft facility to smooth their consumption and borrow against their higher future income to increase their spending on impact relative to other users.[7]

To assess this prediction, we split the sample into quintiles based on the two observable characteristics listed above. We then repeat the baseline DD analysis of Equation (3.1) adding a set of interactions between an indicator for whether the user belongs to the quintile of the respective characteristic and our overdraft treatment variable. To make the results easier to visualize, in Figure 3.3 we report the estimated coefficients and 95% confidence intervals for each interaction term in graphical form.

The left panel reports the effects across quintiles of income growth. The estimated effect does not exhibit any systematic difference for users in the bottom two quintiles compared to users in the top two quintiles, and we do not reject the null hypothesis that the effect is equal across all of the quintiles.

[7] Not only the level but also the uncertainty of the future income path might be relevant to predict spending (Guiso et al., 1992). We tackle this point directly below using past income volatility as well as with a survey instrument to elicit uncertainty about future income flows.

Figure 3.3: Intertemporal Consumption Smoothing?



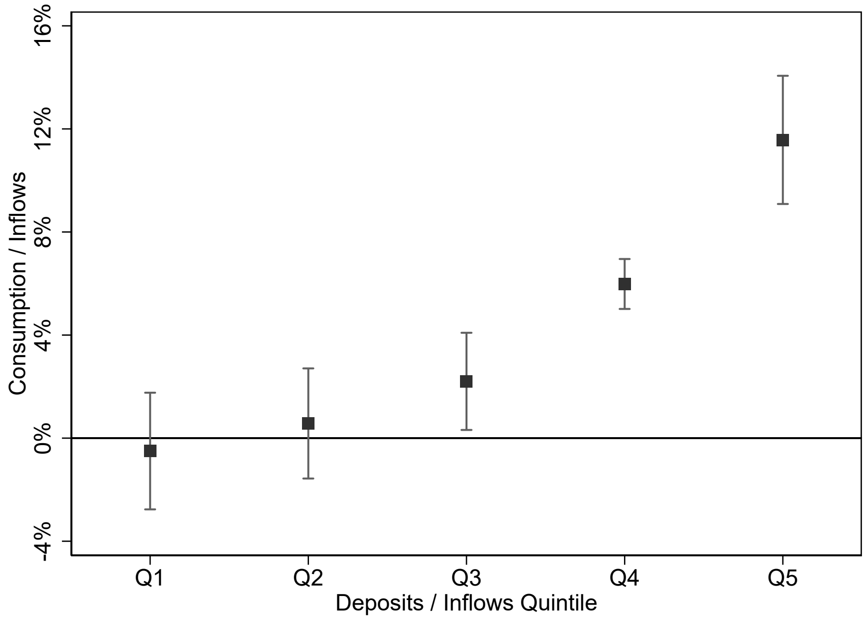
Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the underlying user characteristic. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

In the right panel of Figure 3.3, we split the sample into quintiles by age. Despite the fact that our users are on average younger than the broader population, we still detect substantial differences in age between the bottom quintile and the top quintile, whose averages are about 20 and 45 years. We can plausibly argue that users across these quintiles are on different consumption life-cycle paths. The bottom panel of Figure 3.3, though, vividly shows the lack of heterogeneity of the baseline effect across the age distribution. In terms of magnitudes, we estimate coefficients that range between 3% and 4% in each quintile. Moreover, we cannot reject the null hypothesis that the effects are the same across all quintiles at any plausible level of significance and, if anything, the point estimates are slightly larger for older users, who plausibly face more stable income processes.

3.5.2 Liquidity Constraints? Deposits over Income Flows

Next, we consider the potential role of liquidity constraints in explaining our results (Deaton, 1991). For this analysis, we split the sample by quintiles based on the deposits-to-inflows ratio in the month before activation. We use deposits to inflows as a proxy for liquidity constraints. If liquidity constraints explained our results, we would expect that users with lower deposits-to-inflows ratios would increase their spending

Figure 3.4: Consumption Response by Deposit-to-Inflows Quintile



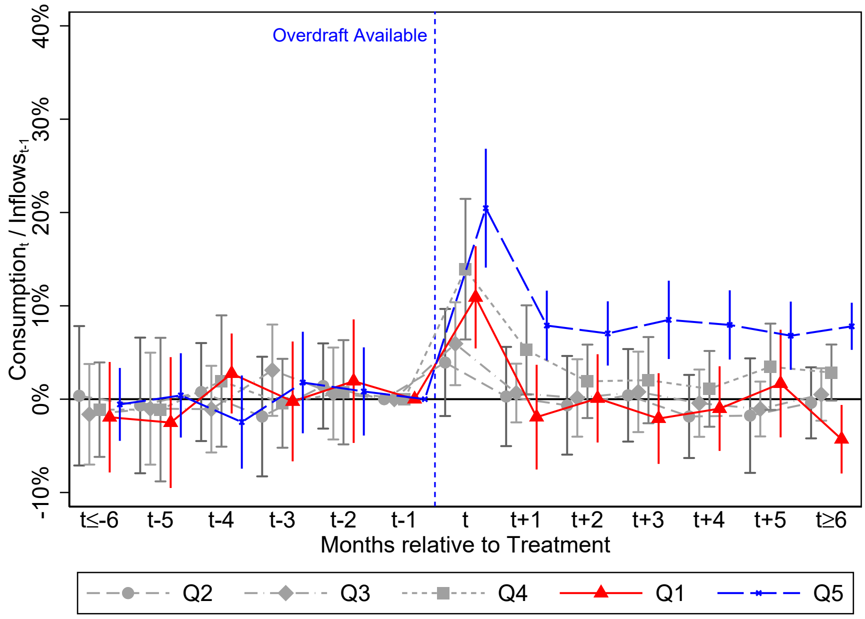
Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft. To generate this plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposits-to-inflows ratio in the month before treatment. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

and tap into negative deposits after accessing the overdraft facility, whereas otherwise similar users with high deposits-to-inflows ratios would barely react.

Figure 3.4 reports the results for estimating the interaction coefficients across quintiles of deposits to inflows. We detect substantial heterogeneity, but the heterogeneity of the effects goes in the *opposite* direction to what liquidity constraints would predict. In fact, the effect of overdraft availability on spending is (insignificantly) negative for users in the bottom quintile—the most liquidity-constrained users—and is zero for those in the second quintile. The effect increases nonlinearly and is disproportionally higher the higher the quintile. The estimated effect is about 2% for users in the third quintile, 5% in the fourth quintile, and 12% in the top quintile. It is the *least* liquidity-constrained users who increase their average spending more after having access to the overdraft facility relative to before.

This pattern is not an anomaly peculiar to users in the top quintile by liquidity: the

Figure 3.5: Consumption Pattern by Deposit-to-Inflows Quintile



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the heterogeneous effect of mobile overdrafts on the consumption behavior of users with different ex-ante liquidity. To generate this plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposits-to-inflows ratio in the month before treatment. We estimate model (1) from Table 3.2 but replace the *Overdraft Available* indicator with separate time dummies, which we further interact with our quintile indicators. Each time dummy marks a one-month period (except for event period $t-1$). Coefficients are normalized by subtracting the pre-treatment mean for each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

positive effect is economically and statistically significant for the median user, and is large also for users in the third and fourth quintiles, which suggests the effect we uncover involves the majority of the sample. We also want to stress that while liquidity-constrained users, the users in quintile 1, do not increase their consumption on average after the activation, they do so on impact in the month post activation and decrease their spending slightly in subsequent months (see Figure 3.5).

In Figure 3.5, we report the estimated coefficients across the deposit-to-inflows quintiles over time. The blue dashed line reports the estimated coefficients for users in the top quintile by deposits to inflows, the red solid line refers to users in the first quintile, and grey lines refer to users in other quintiles. Users in every quintile increase their consumption spending on impact to the availability of the credit line. However, we also see that users in the top quintile increase their spending more than others on impact and that these users increase their spending permanently, that is, their spending does not revert to the pre-activation level over time. We do detect the same permanent effect for users in the fourth quintile, whereas the increase in spending reverts to zero for other users. Importantly, we detect no difference in spending patterns across users before the overdraft facility becomes available.

These consumption patterns suggest that the more liquid users might decrease their savings rate after accessing the overdraft facility, and that this decrease is permanent rather than transitory. We assess this mirroring conjecture by plotting the dynamics of the savings rate across quintiles of liquidity (see Figure C.1 in the Appendix).[8] And, indeed, we find that the savings rate of the most liquid users drops permanently after they get access to the overdraft facility. We do not observe the same permanent pattern for the least liquid users, as well as for users in all other quintiles except for the fourth liquidity quintile.

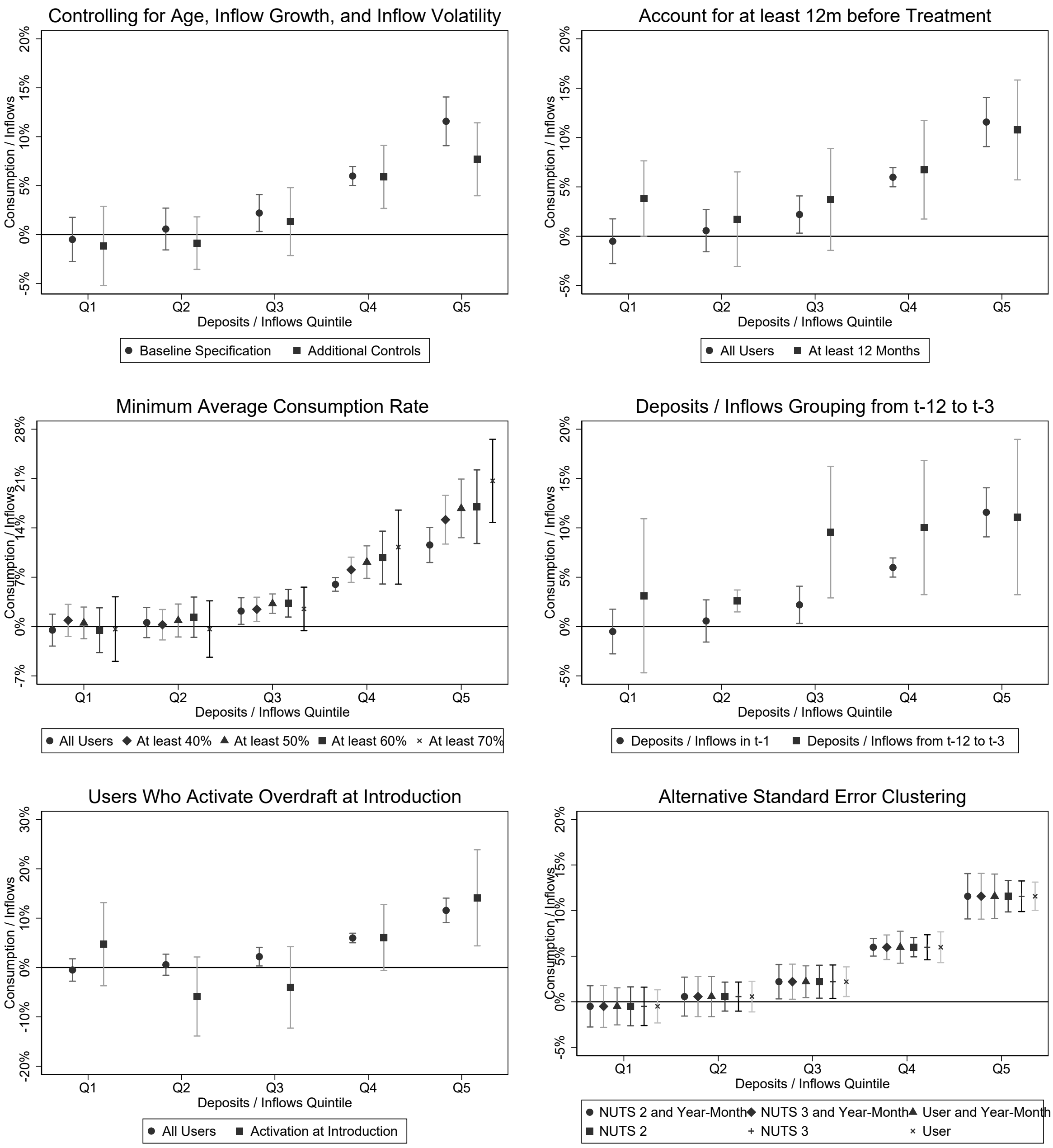
At first sight, the results in Figures 3.4, 3.5, and C.1 are puzzling: the association between users' pre-overdraft liquidity and their spending after overdraft activation seems to go in the *opposite* direction of what we would have expected under a liquidity-constraints explanation. Before digging deeper into the drivers of this empirical regularity, we perform a large set of robustness tests to verify this pattern is a robust feature of the data.

First, in Figure 3.6, we assess the robustness of the consumption pattern by liquidity quintile across a set of relevant subsamples and specifications. In the top left panel, we compare the estimated coefficients and confidence intervals for the baseline specification and a second specification in which we additionally include interaction terms for (i) user age, (ii) inflow growth in the six months before and after overdraft availability, and (iii) inflow volatility in the twelve months prior to the overdraft treatment. We cannot reject the null hypothesis that the coefficients are equal across specifications either economically or statistically.

In the top right panel of Figure 3.6, we compare the baseline effect in the full sample of users to the results when we restrict the working sample only to users with an active account for at least 12 months before the overdraft became available. This test is relevant because one might be concerned that users who drive our effect were merely opening an account to take advantage of the overdraft facility. These users might plan to make larger purchases and move money from other accounts into the online account

[8] We thank Greg Buchak for suggesting that we directly compute the savings rate and examine its evolution over time.

Figure 3.6: Robustness Tests



Notes: The plots follow the methodology of Figure 3.4. In the top left panel, we additionally control for user characteristics at treatment (overdraft available interacted with user age, inflows growth and inflows volatility at treatment). In the top right panel, we keep only users that had an account with the bank for at least 12 months before they activated the overdraft facility. In the middle left panel, we focus on users who exhibit an average consumption rate of at least X% over the sample period where we vary X from 40 to 70. In the middle right panel, we group users into quintiles based on the average deposits-to-inflows ratio from 12 until 3 months before treatment. In the bottom left panel, we focus on users who activate the overdraft at the introduction date and compare them to users who activate the overdraft at least one year after the introduction. In the bottom right panel, we provide baseline regression results for various standard error clusterings. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. Except for the bottom right panel, we double cluster standard errors at the NUTS 2 and year-month level.

resulting in large savings to deposits and large spending responses. As expected, the estimates are substantially noisier in the smaller sample of long-term users, but we replicate our baseline results.

The middle panels of Figure 3.6 consider two forms of measurement error that would be problematic in our setting. First, we do not know whether the financial transactions we observe are all the transactions of our sample users because we cannot rule out for sure that these individuals have accounts at other banks. To alleviate this concern, we repeat the analysis restricting our sample to users whose average spending with our bank equals at least 40%, 50%, 60%, or 70% of their monthly income.[9] Our point estimates are similar and remain statistically significant when we increase this threshold despite the drop in the number of observations.[10]

Second, in the middle right panel of Figure 3.6, we consider the robustness of our results with respect to the definition of our sorting variable—deposits over inflows. Specifically, we assess whether the consumption-liquidity pattern differs depending on whether we sort users based on the ratio measured in the month before the overdraft treatment or the one-month period starting 3 months before activation. We find no detectable difference in the baseline results which ensures that transfers into the account immediately before activation due to future spending plans cannot drive the patterns we document.

In the bottom panels, we show (i) that the statistical significance of our results barely changes across different levels of clustering and (ii) that our results remain robust when we restrict the sample to users who activate the overdraft at the first introduction of the overdraft product by the bank to alleviate the concern that users open accounts with the intention to activate the overdraft.[11]

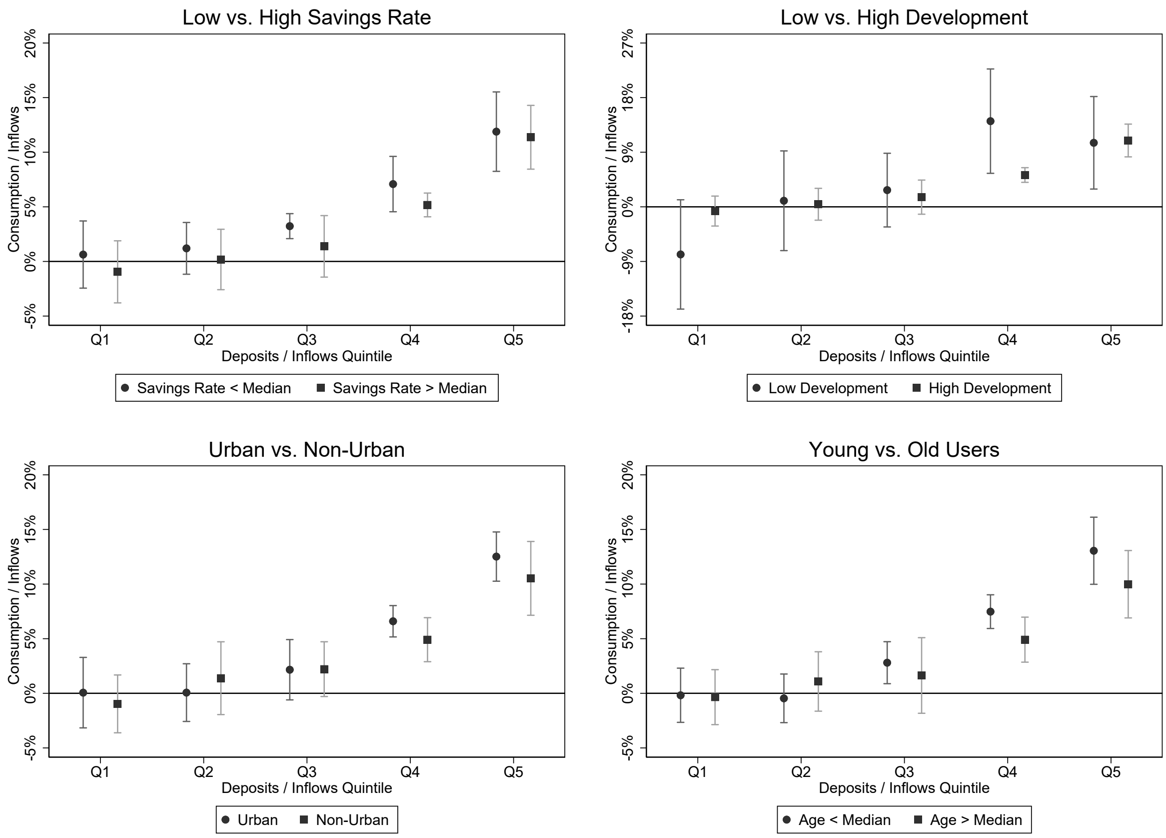
To further assess the robustness of the baseline consumption responses based on deposits to inflows, in Figure 3.7 we compare the estimated coefficients by quintiles across alternative demographic groups to check whether observables might drive the baseline relationship. This test is relevant because it could still be the case that individuals in the top quintiles by deposits to income might have characteristics that according to the PIH would predict a larger consumption response to the availability of credit despite the fact that we do not observe that these characteristics matter

[9] We thank Greg Buchak for suggesting this robustness test.

[10] As an additional (untabulated) test, we exclude all users who have any incoming or outgoing wire transfers other than direct income deposits, which might capture individuals who have other accounts at different institutions. Even in this case, the results barely change.

[11] We thank Michaela Pagel for suggesting these robustness tests.

Figure 3.7: External Validity



Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft for various sample splits. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposits-to-inflows ratio. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

unconditionally. Irrespective of whether we compare users who (i) live in European regions (NUTS 1) with above or below median savings rates (top left panel), (ii) reside in former communist countries or not (top right panel), (iii) live in rural versus urban areas (bottom left panel) [12], or (iv) are young versus old (bottom right panel), we fail to detect any systematic differences in the baseline pattern.

Overall, the fact that users with higher deposits-to-inflows ratios spend more after they have access to the overdraft is a robust feature of the data.

[12]We define urban users as those who live in cities with more than 500,000 inhabitants.

3.5.3 Evidence on Objective Drivers of Precautionary Savings

In the standard life-cycle model, several individual characteristics, which are typically unavailable in observational field data, could predict the spending reaction to overdraft availability. For instance, systematic differences in users' risk aversion, time preferences, beliefs about life expectancy, or bequest motives might drive these results. Moreover, expecting imminent large expenses due to unobserved health reasons, other unobserved reasons, as well as private information about the probability of becoming unemployed and hence having more volatile income streams in the future might all contribute to the observed consumption effects (Gomes and Michaelides, 2005; Chetty and Szeidl, 2007; Carroll, 1997).

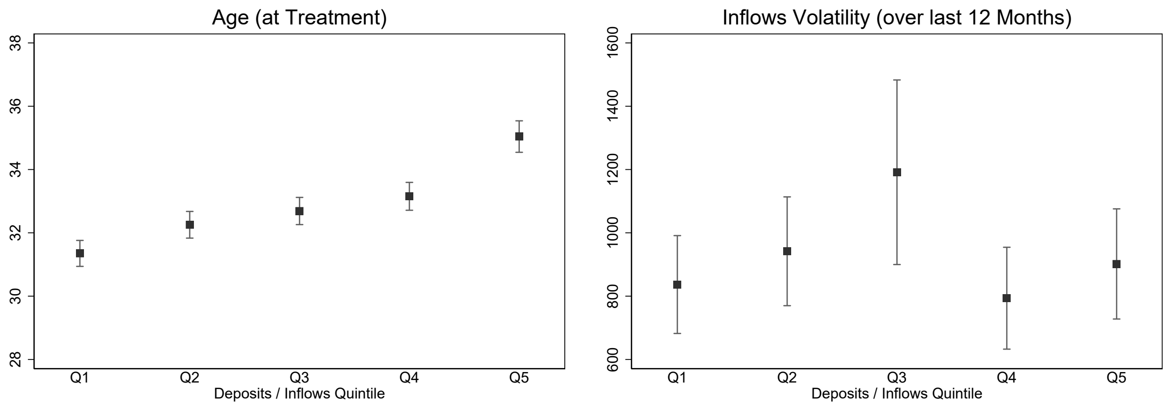
These dimensions either predict larger precautionary savings motives due to preference heterogeneity for a given level of objective uncertainty or might translate into differences in precautionary savings due to subjective needs. Once the overdraft facility becomes available to these users, it might act as a form of insurance and trigger higher spending because users know they can now tap into negative deposits using the overdraft facility if a shock occurs.

In addition to these precautionary savings motives, one can think of other channels that could explain users' willingness to spend liquid assets after they obtain access to the overdraft. For instance, agents might have low financial literacy and might be unable to optimize their allocation of resources over time. Alternatively, users might be distrustful of others and hence display a precautionary savings motive that is not based on their financial characteristics.

In Figure 3.8, we consider two dimensions that might predict differential precautionary savings motives across liquidity quintiles, which we can directly measure in our data. First, we consider age in the left panel. Age increases monotonically with the bins by deposits-to-income inflows, ranging from 31.4 to 35.1. Although the difference between the fifth and first bin is statistically different from zero, the magnitude of this difference is less than 10% of the average age in the top bin. More importantly, though, the typical precautionary savings explanation would suggest that *younger* users have higher precautionary savings motives because these users are likely to have more uncertain income paths, might expect higher future income growth, might face less employment stability, and might still not be in the workforce at all.

Second, we test whether income uncertainty drives our results in the right panel. Specifically, we average the standard deviation of income inflows over the 12 months

Figure 3.8: User Characteristics by Deposits-to-Inflows Quintile



Notes: This figure illustrates the cross-sectional heterogeneity in users' characteristics by deposits-to-inflows quintile. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposits-to-inflows ratio in the month before treatment. Vertical bands represent 95% confidence intervals for the mean of each quintile.

before overdraft facility activation within bins. We do not detect any systematic pattern or difference between the bottom and top bin by deposits to income. This fact is prima facie evidence that differences in income uncertainty do not justify why users in the top bin behave as if they have stronger precautionary savings motives.

We also report descriptive statistics by bins of deposits to inflows in Panel A of Table 3.3. We do not find large differences in demographics such as age or gender. Moreover, we find that lower outflows drive the higher deposits of users with high liquidity rather than higher inflows or higher levels of deposits twelve months ago.

3.5.4 Eliciting Preferences, Beliefs, and Motivations

Considering the other dimensions we discussed in the previous section requires eliciting users' preferences, beliefs, and motivations. To make progress on this front, in June and July 2019 we fielded a survey intervention that we designed to elicit users' risk and time preferences, a large set of beliefs, motivations, perceptions, as well as financial literacy and generalized trust.

Users could answer the elicitation survey either when using the app on their desktop or on their mobile phones. We sent 73,000 survey invitations, targeting a response rate between 10% to 15%, based on other surveys the FinTech bank ran on the platform in the recent past. Overall, we obtained 7,901 responses to the survey, which represents

Table 3.3: User Characteristics by Deposits-to-Inflows Quintile

Panel A: Users' Financial Characteristics

	Deposits / Inflows Quintiles					
	Q1	Q2	Q3	Q4	Q5	SD
Flow Characteristics						
Cumulative Inflows$_{t-12:t-1}$	11,491.77	13,381.19	14,930.03	10,580.58	10,753.34	16,980.36
Inflows$_{t-1}$	1,270.25	1,775.88	1,882.12	1,779.34	1,293.43	3,961.29
Inflows$_{t-12:t-1}$	957.65	1,115.10	1,244.17	881.71	896.11	1,415.03
SD(Inflows$_{t-12:t-1}$)	836.63	941.74	1,191.37	793.55	901.77	1,635.70
SD(Consumption$_{t-12:t-1}$)	392.22	369.24	380.01	307.52	267.60	367.89
Cumulative Outflows$_{t-12:t-1}$	11,778.41	13,135.22	13,767.61	9,589.49	7,774.88	15,500.42
Deposit Characteristics						
Deposits$_{t-1}$	39.45	451.87	1,128.83	1,715.09	4,163.05	8,520.52
Deposits$_{t-12}$	283.02	320.74	468.30	434.86	627.48	1,225.21
Deposits$_{t-12:t-1}$	273.90	459.46	729.29	814.87	2,012.25	2,432.76
Negative Deposits$_{t+1:t+3}$	0.65	0.41	0.29	0.19	0.10	0.47
Account Characteristics						
User Age$_t$	31.35	32.25	32.69	33.15	35.05	9.89
Female	0.20	0.20	0.22	0.25	0.23	0.41
Urban	0.50	0.54	0.56	0.54	0.47	0.50
Account Age$_t$	0.67	0.62	0.61	0.55	0.71	0.36
Users	1,909	1,909	1,910	1,908	1,909	9,545

Panel B: Users' Subjective Beliefs

	Deposits / Inflows Quintiles					
	Q1	Q2	Q3	Q4	Q5	SD
Risk Aversion [0-10]	5.13	4.63	4.47	4.65	4.72	2.31
Trust Level [0-10]	5.29	5.74	5.53	5.31	5.47	2.15
Risk-Return Category [1-4]	2.88	2.85	3.03	2.93	2.86	0.74
Patience [$>$ 100]	118.98	119.07	119.45	121.96	117.48	17.42
Likelihood of Large Expenses [0-10]	4.13	4.29	4.48	4.46	4.80	2.63
Likelihood of Large Medical Expenses [0-10]	2.32	2.26	2.32	2.50	2.45	2.29
Likelihood of Losing Job [0-10]	1.34	1.15	1.41	1.14	1.29	2.12
Health Satisfaction [0-10]	6.99	7.28	7.16	7.02	7.41	2.21
Reasons for Saving [1-4]	2.20	2.26	2.23	2.35	2.29	0.98
Basic Financial Computation Ability [1-3]	2.85	2.72	2.82	2.70	2.69	0.56
Life Expectancy [number]	83.37	85.57	84.70	83.06	83.13	10.63
Users	96	141	112	114	136	599

Notes: This table provides descriptive statistics of user characteristics and survey responses. Panel A provides descriptive statistics for users at the time of overdraft activation, sorted into quintiles based on the ratio of deposits over inflows in the month before activation of the overdraft facility. Subscript t refers to the activation date of each user in our sample. The last column reports the standard deviation of the corresponding characteristic across all users. Panel B reports a set of preferences and beliefs dimensions we elicited from users through an ad-hoc survey intervention. We take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the ratio of deposited amount over income. We limit the sample to users that activate the overdraft facility in our main sample.

a response rate of 11%, in line with survey-based studies. Of the 7,901 respondents, we kept the survey outcomes of users for which we observe the activation of the overdraft facility during our sample period. Overall, we obtain 597 survey responses from users that belong to the baseline consumption sample and have activated the overdraft facility within our time frame.[13]

Importantly, when we approached users, we did not disclose that the aim of the intervention was to link their answers to spending behavior around the introduction of the overdraft facility. Being silent about the overdraft facility was crucial to reduce the concern of experimenter demand effects—the possibility that subjects guess the aim of the experiment and align their answers and choices correspondingly.

The issue of experimenter demand effects is one of the strongest concerns faced by experimental economics and survey-based elicitation tools, as discussed recently, for instance, by De Quidt et al. (2018). Because we did not refer to the overdraft facility in any way within our survey, it is implausible that users would understand that the scope of the experiment was to assess the drivers of their spending and borrowing behaviors and hence could manipulate their answers to our questions. A drawback of the lack of direct reference to the overdraft facility experience is that we could not ask users directly for the motivations they had to activate and use the facility. Because of the issue of demand effects, the answers to such a direct question would have been barely interpretable anyway due to strategic motives in users' answers (see, e.g., D'Acunto, 2018, 2019).

We designed the survey questions following earlier research. We elicited risk aversion by asking users to rank their willingness to take on risks in financial matters on a scale from 1 (very low) to 10 (very high) (see, e.g., Guiso et al., 2008; D'Acunto et al., 019b,c). For time preferences, we gave users a hypothetical choice between a certain amount at the time of the survey or increasing amounts one month later (see, e.g., Benjamin et al., 2010; Coibion et al., 2019). To elicit expectations about upcoming large expenses, we asked users to rank their probability of facing large consumption expenses or large medical expenses over the following 12 months (D'Acunto et al., 019a). We elicited similar rankings for users' expectations about the possibility of losing their job over the following 12 months, which aims to capture uncertainty about future income flows (Guiso et al., 1992), users' satisfaction with their health conditions, and users' generalized trust towards others (see, e.g., Dominitz and Manski, 2007; Guiso et al., 2004; D'Acunto et al., 2018). To elicit users' financial literacy, we asked them to as-

[13]We report the original survey questions in Appendix Table C.2.

sess whether the amount that would compound in their checking account at a certain interest rate would be above or below a given value (see, e.g., Lusardi and Mitchell, 2011). Among the potential questions the literature proposed for assessing financial literacy (Lusardi and Mitchell, 2014), the ability to understand compounding is most relevant for our setting in which we study the borrowing and spending behavior of bank customers that consider the use of a credit line.

Panel B of Table 3.3 reports the results for the basic preferences, beliefs, and motivations we elicited. We sort users into five quintiles based on their deposits-to-inflows ratio before accessing the overdraft facility. We then compute the average quantitative response of these users to the elicitation questions within each bin, which we plot together with the 95% confidence interval of the mean in each quintile in Appendix Figure C.3.

Across the dimensions we elicited, we fail to detect any systematic patterns in the cross-section of liquidity. None of the dimensions we consider, which could have explained the responses in Figure 3.4 in a standard life-cycle consumption–savings model, seems to be able to capture such patterns. Not only are the averages within quintiles not different from each other statistically, but they are also similar in terms of economic magnitude, which suggests that low statistical power in the small survey sample is unlikely to drive the lack of variation across quintiles.

Overall, our evidence based on elicited preferences, beliefs, and motivations directly dismisses the most compelling standard channels that would justify a spending increase by liquid users but not illiquid users once the overdraft facility becomes available to them.

3.5.5 The Perceived Precautionary Savings Mechanism

The heterogeneity results suggest a pattern whereby users with higher liquidity (cash deposits) over income react more than others to the activation of the overdraft facility in terms of spending. This pattern is intriguing because we might have expected the most liquid users to be those that had the least need for an overdraft facility if they wanted to spend more before activation. In contrast, if the overdraft facility is mainly used to smooth spending and alleviate liquidity constraints, users in the bottom liquidity quintile should react most.

Alternatively, users might accumulate liquidity over time because of the perception of possible future needs. Therefore, sorting users at the time of the overdraft activation corresponds to sorting users based on their perceived need of precautionary savings. So far, comparing bins by deposits-to-inflows ratios does not suggest that users in the top bin have any objective reason to have stronger precautionary savings motives than users in the lower bins. We now assess whether users in the top bin also behave in line with precautionary savers in terms of using the overdraft, apart from increasing consumption spending after activating the overdraft facility. Precautionary savers, contrary to liquidity-constrained individuals, would likely not tap into negative deposits and would not increase their debt levels through the overdraft facility. Instead, they should view the facility as a form of insurance against negative income shocks or unexpected expenses and would thus spend some of the existing liquidity they had accumulated before the overdraft facility was available once they knew they could tap into negative deposits if needed. Hence, we would expect a permanent increase in the consumption spending of these high deposits-to-inflows users and a decrease in the savings rate as we indeed observe in the data.

The results in Figure 3.4 are broadly consistent with users in the top liquidity bin behaving as if they had strong precautionary-savings motives. First, these users are substantially less likely than users in lower bins to tap into negative deposits after activation, despite increasing their consumption spending substantially more relative to the pre-period than these other users. The probability of tapping into negative deposits in the three months after activation ranges from 67% for users in the bottom bin to 10% for users in the top bin. Moreover, it is unlikely that a large fraction of the individuals in our sample have objective precautionary savings motives due to potentially unexpected large medical bills or other medical-related expenses because the 75^{th} percentile of age in our sample equals 38.7 years.

A potential concern with our interpretation is that users decide they want to purchase big ticket items and move cash to the deposit account at our bank before they activate the overdraft facility. However, in the data we do not observe heterogeneity in the cumulative inflows at our bank in the three months before activation by deposits to inflows. Moreover, we test directly for this potential alternative interpretation by comparing the change in the ratio of spending on big ticket items over total spending before and after activation of the overdraft facility and across users by liquidity quintiles.[14] Figure C.2 in the Appendix reports the change in this ratio across liquidity quintiles and unveils that, in fact, the ratio has barely changed economically and

[14]For this test, our definition of big ticket items refers to purchases of goods and services which cost above 5,000 Euros. The results are similar if we change this threshold.

statistically for most users. In particular, the change does not display the monotonic pattern by liquidity that we should observe if this explanation was relevant to our results.

Overall, users with a high share of deposits to inflows and hence high liquidity behave as if they had precautionary savings motives and hence accumulated savings and saved a larger share of their income before the overdraft facility became available to them. Once they have access to the overdraft facility which acts like an insurance for additional future spending needs, possibly due to unexpected expenses or income shortfalls, they increase consumption spending. These users, though, do not display any of the characteristics that are typically associated with individuals that have precautionary savings motives, such as high income volatility or higher risk aversion. Based on these considerations, we label the mechanism we document in this paper as *perceived* precautionary savings.

3.5.6 Alternative Explanations and Channels

We move on to consider a set of additional potential alternative interpretations of our results. First, the facility might free up liquid resources users were keeping in their bank accounts because of private information about upcoming individual income shocks. In this vein, even models of buffer-stock savings that allow for both impatience and precautionary savings motives might explain our results at least in part. Our heterogeneity results do not seem fully consistent with this interpretation for a set of reasons. Income uncertainty decreases with age and the heterogeneity results by age we discuss above are not consistent with this form of precautionary-savings motive. Moreover, we find the pre-activation volatility of income flows does not predict the reaction to the availability of credit. Also, as discussed above, users close to the liquidity constraint do not react on average post activation, whereas those farther away from the constraint react the most, and the buffer-stock interpretation predicts the opposite pattern.

A second potential explanation is a buffer-stock model with durable consumption similar to the one Aydin (2015) studies. However, a set of results suggests this interpretation cannot fully explain the results in our setting. In addition to the facts that the least liquidity-constrained users react the most and that we do not see any differential reaction based on pre-activation income volatility, we find users that react the most on average do not tap into negative deposits and hence *de facto* never use the facility.

A third interpretation we consider is present-biased preferences—the fact individuals discount the distant future by more than they discount the immediate future (Meier and Sprenger, 2010). This interpretation by itself is unlikely to explain all our results, because if the individuals that react the most to overdraft activation were present-biased, they would have consumed out of their higher deposits even *before* activating the overdraft facility, which we do not observe in the data.

Contrary to the alternative explanations we have discussed in this section, the perceived precautionary savings channel is consistent with the baseline facts we document as well as with the fact that users at the top of the distribution by deposits over income flows react the most to the activation of the overdraft facility.

At first, our results might appear inconsistent with a large literature documenting users that are most constrained ex-ante react the most to the extension of credit (see, e.g., Agarwal et al., 2017; Aydin, 2015; Gross and Souleles, 2002). The major difference between these studies and our paper is that earlier studies exploited changes in the intensive margin of credit, that is, changing the extent of credit for agents who were already borrowing. We, instead, focus on the extensive margin of credit, that is, providing users with a borrowing facility for the first time. The insurance effect of first-time borrowing facilities could not be detected in earlier research even if this effect was true because all the agents in earlier work were already provided with insurance around the change in credit limits. The insurance mechanism did not change within agents over time in intensive-margin studies reconciling our work with previous findings in the literature.

In our setting, users that previously were most concerned about future unexpected expenses or had higher precautionary savings demands for other reasons that we capture by sorting on deposits to inflows seem to react the most to the provision of a downside insurance mechanism—the overdraft facility.

3.6 Regression Discontinuity Analysis

An important identification concern with our analysis so far is the endogenous timing at which users open their accounts. One might worry that users activate the account only when they foresee the need for an overdraft facility, for instance when they plan to have larger-than-usual upcoming expenses.

We provide tentative evidence that this endogeneity concern might not be as relevant in our setting as one might worry. To do so, we repeat our tests by restricting the sample only to users who activated their overdraft facility within one month after the online bank made it available.[15] The rationale for this test is that users who activate the facility as soon as it is available might be less likely to have planned to activate it in view of large upcoming expenses because they could not know the fact that the bank would have provided such facility nor the timing. We report the results for this test in Figure 3.6 (bottom left panel). Although this test restricts the baseline sample substantially, and hence increases our estimated standard errors, the baseline spending patterns by liquidity quintiles are quite similar to the baseline analysis in terms of economic magnitudes, and the coefficients for the two top quintiles, just like in the baseline analysis, are statistically different from zero.

Despite this evidence, one might worry that other omitted variables might simultaneously impact users' consumption behavior and overdraft activation decision, giving rise to a spurious relation between the two. One example for such a correlated omitted variable might be time-varying, user-specific exposure to television commercials that independently advertise the bank's overdraft, and various consumer products, even for users who have been banking with our provider for quite some time and hence do not open new accounts.

To directly address these endogeneity concerns, in this last part of the paper we estimate the causal effects of the availability of the mobile overdraft on spending in a sharp RDD that exploits variation in users' overdraft limits based on thresholds embedded in the bank's credit allocation algorithm. Our sharp RDD conditions the analysis on users' (possibly endogenous) selection into the mobile overdraft and relies on exogenous variation in the size of the credit line along the intensive margin.

We do not implement this design for the baseline analysis of the paper because we can only exploit a limited number of users in the sample for the RDD setting. By construction, as we discuss in more detail below, the RDD only uses users who are close to pre-specified thresholds based on the algorithm that assigns the overdraft amount to those activating an overdraft facility. Because of the limited sample, any meaningful statistical analysis of heterogeneity and variation across subgroups of users would be impossible.

[15]We thank Michaela Pagel and Greg Buchak for suggesting this test.

3.6.1 Credit Allocation Algorithm

The bank's credit allocation process consists of two steps. First, the bank determines whether users pass all exclusion criteria and are thus eligible for a mobile credit line. Overdraft applicants receive a credit line if they (i) are employed, (ii) live in countries where the bank offers a mobile overdraft, (iii) have a minimum credit score of F, and (iv) if their checking account did not trigger any direct debit reversals. The bank obtains credit scores from consumer credit bureaus, which collect information on users' credit histories to estimate default probabilities and assign individual credit ratings from A (lowest default risk) to M (highest default risk). A credit score of F implies that the individual has an estimated default probability of less than 10 percent.

Second, the bank determines the maximum overdraft amount for each eligible user based on the applicant's credit score and average account income according to the following formula:

$$\text{Overdraft Amount} = \begin{cases} \text{Max Limit} & \text{if } 2 \times \text{Income} \geq \text{Max Limit} \\ \text{Min Limit} & \text{if } 2 \times \text{Income} \leq \text{Min Limit} \\ 250 \times \lfloor \frac{2 \times \cdot \text{Income}}{250} \rceil & \text{otherwise,} \end{cases} \quad (3.2)$$

where $\lfloor x \rceil$ rounds the number x to the nearest integer.

For each rating notch between A and F, the bank specifies a lower (*Min Limit*) and upper limit (*Max Limit*) for each user's allocated credit amount. Income is a linear function of the user's different inflow types in the months prior to the overdraft application. Our data sharing agreement with the bank does not allow us to report the rating-specific overdraft limits or the precise formula that transforms users' account inflows into income. However, we can disclose that the bank differentiates between regular salary and non-salary related inflows (e.g., pensions, child benefits, study support from parents, etc.) and puts a higher weight on the former. The lower and upper overdraft limits monotonically increase in the customer's credit rating and range between 500 and 5,000 Euros.

To determine each user's maximum available overdraft amount, the bank's fully automated credit allocation algorithm multiplies the *Income* variable by 2. If the resulting value exceeds (falls below) the upper (lower) credit limit, the maximum overdraft amount is bounded from above (below) by the rating-specific limit. If the doubled income falls between the upper and lower limit, the amount is rounded to the closest

250 Euro multiple at the midpoint. Panel A of Figure 3.9 illustrates the rounding convention embedded in the credit algorithm. For example, if overdraft applicant A has a salary of 2,100 Euros and no additional account inflows, her implied overdraft amount after multiplying the income by 2 equals 4,200 Euros which, if rounded to the closest 250 Euro threshold, translates into a maximum available overdraft amount of 4,250 Euros (assuming that the upper and lower credit limits do not bite). The bank's credit allocation process gives rise to 18 unique thresholds within the interval between 500 and 5,000 Euros, at which the maximum overdraft amount jumps discontinuously by 250 Euros. At these thresholds, users with almost identical incomes who find themselves on opposite sides of the rounding threshold receive different overdraft limits for plausibly exogenous reasons. Crucially, users are not aware of the algorithm and the algorithm is fully automated leaving no room for human intervention.

3.6.2 Empirical Implementation

We limit our analysis to users whose maximum overdraft amount equals the individual's income multiplied by two and rounded to the nearest multiple of 250. That is, we drop all users whose transformed income exceeds or falls below the upper or lower credit limit (within the given rating notch) such that the rounding thresholds embedded in the bank's credit allocation algorithm do not affect the maximum overdraft amount. For each user in our RDD sample, we compute the forcing variable X_i, which quantifies the individual's distance (in Euros) to the nearest rounding threshold. X_i removes differences in absolute rounding thresholds across individuals and is centered around zero. Users with $X_i \geq 0$ are treated and receive a maximum overdraft amount that is 250 Euros higher than those of control users for whom $X_i < 0$. The probability that a user's overdraft limit gets rounded up by 250 Euros changes discontinuously from 0 to 1 at the rounding threshold. Panel B of Figure 3.9 illustrates the exact treatment rule of our sharp RDD and plots users' treatment assignment for different values of the forcing variable X_i. In areas close to the rounding threshold (where $X_i = 0$), treated and control users have almost identical income profiles.

To examine the causal effect of mobile credit lines on users' consumption behavior, we implement the following sharp RDD

$$\tau \equiv \mathbb{E}\left(C_i(1)|X_i = 0\right) - \mathbb{E}\left(C_i(0)|X_i = 0\right). \tag{3.3}$$

τ is the RD treatment effect and $C_i(1/0)$ is the change in treated (1) or control (0) users' average consumption three months before and after the credit allocation decision, divided by the individual's average inflows in the three months prior to the overdraft application. To estimate this model, we fit a weighted least squares regression of the observed consumption change on a constant and polynomials of X_i on both sides of the rounding threshold. The RD treatment effect is the difference in estimated intercepts from these two local weighted regressions. Formally, each user's consumption change equals

$$C_i = \begin{cases} C_i(0) & \text{if } X_i \geq 0 \\ C_i(1) & \text{if } X_i < 0. \end{cases} \tag{3.4}$$

We focus on observations within the interval $[-h, h]$ around the rounding threshold, where $h > 0$ denotes our bandwidth. The kernel function $K(\cdot)$ specifies our regression weights. $\hat{\mu}_{+/-}$ is the estimate of $\mathbb{E}\left(C_i(1/0)|X_i = 0\right)$ for observations above or below the threshold, which we define as:

$$\hat{C}_i = \hat{\mu}_{+/-} + \sum_{j=1}^{p} \hat{\mu}_{+/-,j} X_i^j. \tag{3.5}$$

p denotes to the order of the local polynomial. The RD treatment effect then equals:

$$\hat{\tau} = \hat{\mu}_{+} - \hat{\mu}_{-}. \tag{3.6}$$

To operationalize the RD estimator, we need to specify (i) the order of polynomial p, (ii) the kernel function $K(\cdot)$, and (iii) the bandwidth h. We follow Gelman and Imbens (2018) and only use polynomials of order 1 and 2 to avoid overfitting issues. We apply weights from a triangular kernel because it is the mean squared error (MSE) minimizing choice for point estimation in our context (Cheng et al., 1997). Finally, we employ the MSE-optimal bandwidth selection procedure recommended by Calonico et al. (2014), which corrects for the bias resulting from subjective bandwidth choices. We residualize the outcome variables of our RD analysis with NUTS 3 $\times$ year-month fixed effects to ensure that we compare treated and control users from the same European country at a similar point in time.

3.6.3 Treatment Manipulation and Balancing Tests

Our sharp RDD critically relies on the assumption that the forcing variable for individuals just below the threshold is similar to those just above the threshold. If users can manipulate the forcing variable and thereby their assignment to treatment and control groups, this local continuity assumption is violated, which results in biased RD estimates (Roberts and Whited, 2013).

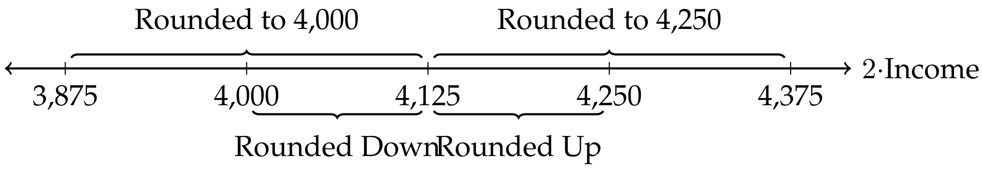
Conceptually, it is unlikely users can control their treatment assignment in our setting. Most importantly, the bank's credit allocation algorithm is proprietary information and overdraft users do not know it. Even if individuals were informed about the precise inner workings of the overdraft allocation formula (in particular its rounding thresholds), it seems implausible they could precisely manipulate their income, for example, by negotiating a higher wage with their employer (Lee and Lemieux, 2010).

To formally assess the validity of the local continuity assumption, we test for the presence of a discontinuity in the density of X_i at the rounding threshold. If users systematically inflate their income to receive a higher overdraft limit, we should observe a kink in the distribution of our forcing variable to the right of the threshold. We use the local polynomial density estimator of Cattaneo et al. (2017) to test whether overdraft users manipulate their assignment into treatment and control group. In Appendix Figure C.4, we plot both the frequency distribution (Panel A) and density function based on quadratic local polynomials (Panel B) of our running variable and do not find graphical evidence for bunching above the rounding threshold. In Figure C.5 in the Appendix, we report the estimation results of the formal treatment manipulation test by Cattaneo et al. (2017) for different polynomial and bandwidth choices. In all specifications, we fail to reject the null hypothesis that our running variable is locally continuous around the rounding threshold.

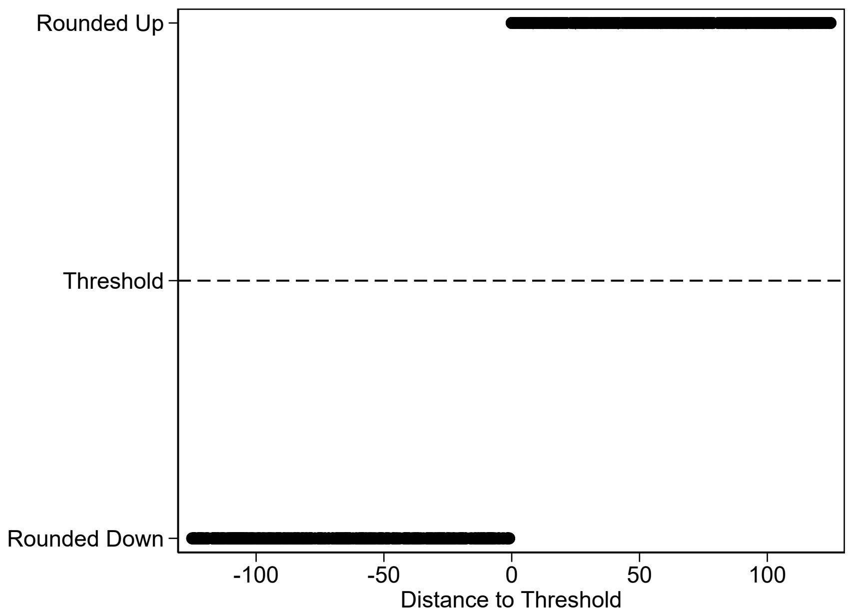
The local continuity assumption implies individuals below and above the cutoff should not only be similar in terms of the forcing variable but also along other characteristics. Since overdraft users lack the ability to precisely manipulate their distance to the rounding threshold, no systematic differences in observable characteristics between the two groups of individuals should exist. Consistent with this argument, we do not find significant differences in the average age, gender, time since account opening, account inflows, and consumption between treated and control users prior to the activation of the mobile overdraft. As an alternative balancing test, we repeat our RD analysis but replace our main outcome variable with each observable user character-

Figure 3.9: Treatment Assignment in Regression Discontinuity Analysis

Panel A: Rounding Logic of Overdraft Allocation Algorithm



Panel B: Visualization of Sharp Treatment



Notes: This figure illustrates how we assign users to the treatment and control groups in our regression discontinuity analysis based on discrete rounding thresholds embedded in the bank's credit risk model. Panel A visualizes the rounding logic of the overdraft allocation algorithm. Panel B plots users' treatment probability for different values of our forcing variable X_i.

Table 3.4: Assessing RDD Identification Assumptions

Panel A: Treatment Manipulation Tests

		Bandwidths		Effective N		Test	
		Left	Right	Left	Right	T-Stat.	p-Value
$h_- \neq h_+$	$T_2(\hat{h}_1)$	104.17	76.21	373	328	-0.94	0.35
	$T_3(\hat{h}_2)$	75.73	82.98	285	345	-0.85	0.39
	$T_4(\hat{h}_3)$	89.01	55.32	322	221	0.39	0.70
$h_- = h_+$	$T_2(\hat{h}_1)$	111.32	111.32	424	448	-0.05	0.96
	$T_3(\hat{h}_2)$	71.59	71.59	248	289	-0.51	0.61
	$T_4(\hat{h}_3)$	58.32	58.32	201	229	-0.59	0.56

Panel B: User Characteristics around Rounding Thresholds

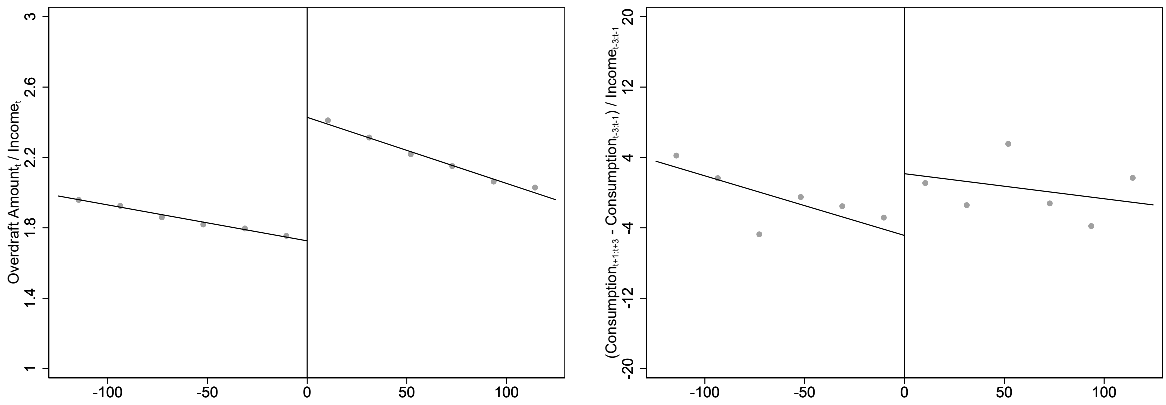
	Rounded Up			Rounded Down			Difference in Means	
	Mean	SD	Median	Mean	SD	Median	Diff.	t-Stat.
User Age [Years]	32.32	9.34	29.91	33.02	10.12	30.37	0.70	1.13
Female [0/1=Yes]	0.25	0.43	0.00	0.24	0.43	0.00	-0.01	-0.35
Account Age [Years]	0.87	0.38	0.83	0.85	0.41	0.79	-0.01	-0.53
$\text{Inflows}_{t-3:t-1}$ [Euro]	1,405.64	1,530.10	1,101.67	1,458.92	1,454.29	1,069.67	53.28	0.56
$\text{Consumption}_{t-3:t-1}$ [Euro]	558.89	522.39	427.17	620.04	597.38	482.83	61.14*	1.70
Users	500			474			974	

Notes: This table provides the results of tests assessing our RDD identification assumptions. Panel A reports the results of treatment manipulation tests using the local polynomial density estimator by Cattaneo et al. (2017). $T_q(h_p)$ denotes the q-th order local polynomial test with bandwidth h_p. *Bandwidth* is the mean-squared-error (MSE) optimal bandwidth, *Effective N* is the effective sample size on each side of the threshold, and T is the two-sided test statistic with corresponding p-value. The tests in the first three rows allow for different bandwidths on each side of the threshold, while the tests in the last three rows impose a common bandwidth on both sides of the threshold. Panel B provides descriptive user characteristics for individuals above (*Rounded Up*) and below (*Rounded Down*) the RD rounding threshold. For each variable, we report the mean, standard deviation (SD), and median (P50) values. In the last two columns, we test for differences in means across both types of users. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

istic. In Table C.4 of the Appendix, we document that the RD treatment effect for all our covariates is economically and statistically indistinguishable from zero.

Overall, the evidence in this subsection indicates that overdraft users do not manipulate their treatment assignment and that individuals above and below the rounding threshold have similar observable characteristics. Both findings suggest the local continuity assumption is satisfied and thereby corroborates the internal validity of our sharp RD design.

Figure 3.10: Regression Discontinuity Results



Notes: This figure provides graphical evidence for the sharp discontinuity in users' overdraft limits and consumption growth rates at the rounding threshold. In Panel A, we plot the income-normalized overdraft limit that users receive at the treatment date. In Panel B, we plot users' consumption growth rate, which we define as the difference in average consumption three months before and after the treatment, normalized by the average account inflows three months prior to the overdraft application. We aggregate our data into 12 disjoint bins, calculate the average value, plot this value above the midpoint of each bin, and separately fit two linear regressions through all observations on each side of the rounding threshold.

3.6.4 RD Consumption Effect

In Figure 3.10, we graphically illustrate the RD treatment effect of a 250 Euro higher overdraft limit on users' consumption behavior. We aggregate our data into disjoint bins and make sure each bin contains either treatment or control observations. We then calculate the average value of our outcome variable, plot this value above the midpoint of the bin, and separately fit two linear regressions through all observations on each side of the rounding threshold.

In Panel A of Figure 3.10, we verify that individuals just above the threshold indeed receive a higher maximum overdraft amount (relative to their income) compared to users just below the threshold. The slope of both fitted regression lines is negative since, within treatment and control group, individuals with larger values of our forcing variable X_i have a higher income, which we use to normalize users' overdraft limit. In Panel B, we plot the change in average (normalized) consumption three months after and before the user obtained access to the credit line. We find a positive discontinuity in users' consumption growth right at the rounding threshold, indicating treated users consume more relative to control users following the exogenous assignment of a 250 Euro higher overdraft limit. In Table 3.5, we present the coefficients from estimat-

Table 3.5: Consumption Growth around Rounding Thresholds

Dependent Variable (×100):	$\frac{\text{Consumption}_{t+1:t+3} - \text{Consumption}_{t-3:t-1}}{\text{Inflows}_{t-3:t-1}}$			
	(1)	(2)	(3)	(4)
Conventional	17.63**	23.48**	17.96**	23.70**
	(2.19)	(2.20)	(2.12)	(2.34)
Robust	21.56**	26.52**	21.83**	26.62**
	(2.37)	(2.31)	(2.31)	(2.46)
Covariates	No	No	Yes	Yes
User Observations	876	876	876	876
Order Local Polynomial (p)	1	2	1	2
Order Bias (q)	2	3	2	3
Bandwidth Left	25.47	35.89	23.98	36.86
Bandwidth Right	25.47	35.89	23.98	36.86

Notes: This table presents non-parametric estimates for the RD treatment effect of a 250 Euro higher overdraft amount on users' consumption behavior. The dependent variable is the difference in average consumption three months before and after the treatment, normalized by the average account inflows three months prior to the overdraft application. We residualize users' consumption growth rate with country × year-month fixed effects to ensure that we compare treated and control users from the same European country at a similar point in time. We only use polynomials of order 1 and 2 to avoid over-fitting issues (Gelman and Imbens, 2018), apply weights from a triangular kernel because it is the mean squared error (MSE) minimizing choice (Cheng et al., 1997), and employ the MSE-optimal bandwidth selection procedure recommended by Calonico et al. (2014). We report both conventional and robust RD estimates (Calonico et al., 2014, 2019). In columns (1) and (2), we do not add any covariates. In columns (3) and (4), we control for *User Age*, gender (*Female*), and *Account Age*. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

ing the sharp RD design we formalized in Equations (3.3) to (3.6). We estimate first- and second-order polynomial regressions at the rounding threshold and report both bias-corrected and conventional t-statistics (Cattaneo et al., 2017; Gelman and Imbens, 2018). In columns (1) and (2), we document a positive and highly statistically significant RD treatment effect on users' consumption growth. The coefficient estimates do not attenuate when we add user characteristics as control variables in a linear and additive-separable way. In line with Calonico et al. (2019), we find adding covariates increases the precision of our point estimates, which again suggests the local continuity assumption is satisfied.

We conduct two robustness tests to assess the sensitivity of our RD estimates. First, we examine how sensitive the RD results are with respect to the choice of our bandwidth (Imbens and Lemieux, 2008). Varying the bandwidth is only meaningful over small intervals around the MSE-optimal choice (Cattaneo et al., 2020). Bandwidths much larger than the MSE-optimal bandwidth bias the RD estimator, while substantially smaller bandwidths inflate its variance. Figure C.6 in the Appendix shows that different bandwidth choices neither substantially affect the magnitude of the point estimate nor its significance. Second, we assess how robust our RD point estimates are to excluding data close to the threshold (see, e.g., Barreca et al., 2011, 2016). We drop users located within the radius $r > 0$ of the rounding cutoff, that is, we exclude observations for which $|X_i| \leq r$ (Cattaneo et al., 2020). Appendix Figure C.7 plots the coefficient estimates for different choices of r and shows that observations close to the rounding threshold do not drive our results. Taken together, the RD results confirm our baseline findings and alleviate concerns that selection into the app to obtain access to a line of credit in anticipation of upcoming expenses drive our results.

3.7 Conclusion

We study the consumption response to the introduction of an overdraft facility on a FinTech app. The average user increases her consumption spending over income by 4.5 percentage points on impact relative to similar users that have access to the overdraft facility at a later point in time. The increase in consumption has a permanent component and we observe a reallocation of consumption from discretionary to non-discretionary expenses.

The surprising result is that we find a large spending response for users with high liquid savings, whereas the users with the lowest amount of liquid savings barely react at all to the provision of the overdraft facility. We do not detect any heterogeneity in preferences or beliefs across liquidity quintiles nor heterogeneity in standard theoretical drivers of precautionary savings motives. These results are not fully consistent with myopic consumers, models with financial constraints, buffer stock models (with durables), and the canonical life-cycle permanent income model.

When we study heterogeneity in the response by observables, we observe a similar response for young and old users, for users with low and high income volatility, and for users with steep and flat income paths.

We argue that a *perceived* precautionary savings channel might be at work for users with high deposits over inflows. Before the facility is available, they perceive high income risk or future expenses and consequently save. Once the overdraft facility is available, which acts like an insurance against future shortfalls, they increase their consumption substantially but in fact barely make use the overdraft facility.

Our findings open new paths for future research. What are the microfoundations of perceived precautionary savings motives? In particular, does this attitude result from biased beliefs about the likelihood of future negative states of the world. Or can modified versions of the neoclassical consumption model predict the patterns we uncover? In terms of policy and real-world applications, do perceived precautionary savings change the effectiveness of conventional fiscal policy such as tax rebates? And could policies be designed to insure perceived precautionary savers in bad times and nudge them to spend their cash in times in which higher aggregate demand is needed?

3.8 Acknowledgments

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A Appendix to 'Crowdfunding and Demand Uncertainty'

A.1 Proofs

Proof of Lemma 1. The proof is essentially the same as in Harris and Raviv (1981). Let $\gamma^*(\mathbf{v}) = (\mathbf{x}^*(\mathbf{v}), \mathbf{t}^*(\mathbf{v}))$ be a solution to the entrepreneur's problem in (1.36). Given this solution, there are $N! - 1$ other solutions which are the same as $\gamma^*(\mathbf{v})$ except that the consumers are rearranged, that is, the elements of $\mathbf{v}$ are rearranged. Since problem (1.36) is a linear program, any convex combination of solutions again yields a solution to problem (1.36). Averaging over all these N solutions therefore yields again a solution which leads to the same payoffs as $\gamma^*(\mathbf{v})$. □

Proof of Lemma 2. To see $t_1^*(0, \mathbf{v}_{-1}) = 0$ notice that any positive transfer violates the individual rationality constraint of consumer 1 with a valuation of zero. To see $x_1^*(0, \mathbf{v}_{-1}) = 0$, suppose $x_1^*(0, \mathbf{v}_{-k}) = 1$ holds. Lowering $x_1^*(0, \mathbf{v}_{-1})$ to zero then increases the entrepreneur's objective by $\pi(0, \mathbf{v}_{-1})c$ while it also relaxes all other constraints where it enters. □

Proof of Proposition 1. Recall that v_1^r denotes the report of consumer 1 and $\mathbf{v}_{-1}^r$ denotes the reports of all consumers other than consumer 1. In line with the incentive compatibility condition assume that $\mathbf{v}_{-1}^r = \mathbf{v}_{-1}$, that is, all other consumers than consumer 1 report truthfully. The 'punish them all' mechanism states that $x_1(v_1^r, \mathbf{v}_{-1}) = t_1(v_1^r, \mathbf{v}_{-k}) = 0$ and $x_k(v_1^r, \mathbf{v}_{-1}) = t_k(v_1^r, \mathbf{v}_{-k}) = 0$ for all $k \in \mathcal{N}$ if $v_1^r \notin \mathbf{v}_{-k}$ (i.e., the entrepreneur does not produce unless all consumers with a positive valuation report the same valuation). Next, I verify that this punishment can be used to sustain full rent extraction in all four possible scenarios of the expected net surplus.

First, consider the case where only the demand states (n_H, v_H) or (n_L, v_H) (or both) yield positive profits. The entrepreneur extracts the full surplus by setting $t_1(v_L, \mathbf{v}_{-1}) = x_1(v_L, \mathbf{v}_{-1}) = 0$, $t_1(v_H, \mathbf{v}_{-1}) = v_H$ and $x_1(v_H, \mathbf{v}_{-1}) = 1$. All viable demand states receive financing, but consumers with a low valuation never receive a product, whereas consumers with a high valuation never receive an information rent.

Second, consider the case where both demand states (n_H, v_H) and (n_H, v_L) yield positive profits. The entrepreneur extracts the full surplus by setting, in addition to the above requirements, $t_1(v_L, \mathbf{v}_{-1}) = v_L$, $x_1(v_L, \mathbf{v}_{-1}) = 1$, $t_1(v_H, \mathbf{v}_{-1}) = v_H$ and $x_1(v_H, \mathbf{v}_{-1}) = 1$ as long as n_H consumers report either v_L or v_H. As long as the other consumers report truthfully, truth-telling is also weakly optimal for individual 1 and all incentive and individual rationality constraints are satisfied with equality.

Third, consider the case where the three demand states (n_H, v_H), (n_H, v_L) and (n_L, v_H) yield positive profits. The entrepreneur extracts the full surplus by setting $t_1(v_L, \mathbf{v}_{-1}) = v_L$ and $x_1(v_L, \mathbf{v}_{-1}) = 1$ if n_H consumers report v_L, or $t_1(v_H, \mathbf{v}_{-1}) = v_H$ and $x_1(v_H, \mathbf{v}_{-1}) = 1$ if n_L n_H consumers report v_H. Again, as long as the other consumers report truthfully, truth-telling is weakly optimal for individual 1 and all consumer constraints are satisfied with equality. □

Proof of Lemma 3. By Lemma 1 and 2, no consumer with a positive valuation has an incentive to report a zero valuation as they do not receive any product. I am left with analyzing whether a consumer with valuation v_L has an incentive to report v_H, and vice-versa, given his beliefs about other consumers' reports. I consider three types of beliefs:

(a) All other consumers with a positive valuation report a different valuation than consumer 1, that is, $v_1^r \notin \mathbf{v}_{-1}^r$.

(b) Some other consumers with a positive valuation report a different valuation than consumer 1, while the remaining other consumers with a positive valuation report the same valuation as consumer 1, that is, $v_1^r = v_{-1}^r$ for some $v_{-1}^r \in \mathbf{v}_{-1}^r$ with $v_{-1}^r > 0$.

(c) All other consumers with a positive valuation report the same valuation as consumer 1, that is, $v_1^r = v_{-1}^r$ for all $v_{-1}^r \in \mathbf{v}_{-1}^r$ with $v_{-1}^r > 0$.

To see part (i) of the Lemma, consider the individual rationality constraint of consumer 1 with v_L which implies $t_1^*(v_L, \mathbf{v}_{-1}^r) = v_L x_1^*(v_L, \mathbf{v}_{-1}^r)$ for all $\mathbf{v}_{-1}^r$. The incentive compatibility constraint of consumer 1 with v_L then reduces to $t_1^*(v_H, \mathbf{v}_{-1}^r) \geq v_L x_1^*(v_L, \mathbf{v}_{-1}^r)$ for all $\mathbf{v}_{-1}^r$. Truthful reporting is hence weakly optimal for consumer 1 with valuation v_L regardless of his beliefs about $\mathbf{v}_{-1}^r$.

To see parts (ii) and (iii), I plug $t_1^*(v_L, \mathbf{v}_{-1}^r) = v_L x_1(v_L, \mathbf{v}_{-1}^r)$ into the incentive compatibility constraint of consumer 1 with a high valuation, which yields $t_1^*(v_H, \mathbf{v}_{-1}^r) = v_H x_1^*(v_H, \mathbf{v}_{-1}^r) - (v_H - v_L) x_1^*(v_L, \mathbf{v}_{-1}^r)$ and satisfies both the individual rationality constraint of consumer 1 with v_H and the inequality $t_1^*(v_H, \mathbf{v}_{-1}^r) \geq v_L x_1^*(v_L, \mathbf{v}_{-1}^r)$ as long as $x_1^*(v_H, \mathbf{v}_{-1}^r) \geq x_1^*(v_L, \mathbf{v}_{-1}^r)$. Again, truthful reporting is weakly optimal for consumer 1 with valuation v_H for all possible beliefs about $\mathbf{v}_{-1}^r$.

Finally, note that $t_1^*(v_H, \mathbf{v}_{-1}^r) = v_H x_1^*(v_H, \mathbf{v}_{-1}^r)$ can only be a solution if $x_1^*(v_L, \mathbf{v}_{-1}^r) = 0$ as it implies both $t_1^*(v_L, \mathbf{v}_{-1}^r) \geq v_H x_1^*(v_L, \mathbf{v}_{-1}^r)$ through the incentive compatibility constraint of consumer 1 with valuation v_H, as well as $t_1^*(v_L, \mathbf{v}_{-1}^r) \leq v_L x_1^*(v_L, \mathbf{v}_{-1}^r)$ through the individual rationality constraint of consumer 1 with v_L. Combining both inequalities yields a contradiction except if $t_1^*(v_L, \mathbf{v}_{-1}^r) = x_1^*(v_L, \mathbf{v}_{-1}^r) = 0$. □

Proof of Proposition 2. The proof proceeds by considering the four possible scenarios of the expected net surplus and deriving the conditions under which the entrepreneur optimally implements first-best allocations using the belief-robust mechanism.

First, consider the case where only the demand states (n_H, v_H) or (n_L, v_H) (or both) yield positive profits. The entrepreneur maximizes profits and extracts the full surplus by setting $t_1^*(v_L, \mathbf{v}_{-1}^r) = x_1^*(v_L, \mathbf{v}_{-1}^r) = 0$, $t_1^*(v_H, \mathbf{v}_{-1}^r) = v_H$ and $x_1^*(v_H, \mathbf{v}_{-1}^r) = 1$. All viable demand states receive financing, but consumers with a low valuation never receive a product, whereas consumers with a high valuation never receive an information rent. The mechanism exhibits truthful behavior of all consumers for all beliefs $\mathbf{v}_{-1}^r$ (by Lemma 3) and implements first-best allocations in this case.

Second, consider the case where both demand states (n_H, v_H) and (n_H, v_L) yield positive profits. The entrepreneur chooses between setting $t_1^*(v_L, \mathbf{v}_{-1}^r) = t_1^*(v_H, \mathbf{v}_{-1}^r) = v_L$ or $t_1^{**}(v_H, \mathbf{v}_{-1}^r) = v_H$ and $t_1^{**}(v_L, \mathbf{v}_{-1}^r) = 0$. While the former entails first-best production decisions $x_1^*(v_L, \mathbf{v}_{-1}^r) = x_1^*(v_H, \mathbf{v}_{-1}^r) = 1$ and expected profits

$$\mathbb{E}\left[\Pi(\gamma^*(\mathbf{v}))\right] = \pi_n \left[n_H(v_L - c) - I\right], \tag{A.1}$$

the latter involves $x_1^{**}(v_L, \mathbf{v}_{-1}^r) = 0$ and $x_1^{**}(v_H, \mathbf{v}_{-1}^r) = 1$ with expected profits

$$\mathbb{E}\left[\Pi(\gamma^{**}(\mathbf{v}))\right] = \pi_n \pi_v \left[n_H(v_H - c) - I\right]. \tag{A.2}$$

The entrepreneur therefore strictly prefers to implement first-best allocations in this case, if Equation (A.1) exceeds Equation (A.2), that is, if

$$(1-\pi_v)\left[n_H(v_L-c)-I\right] > \pi_v n_H\left(v_H-v_L\right). \tag{A.3}$$

Again, both strategies are consistent with Lemma 3.

Third, consider the case where the three demand states (n_H, v_H), (n_H, v_L) and (n_L, v_H) yield positive profits. If the entrepreneur sets $t_1^{***}(v_L, \mathbf{v}_{-1}^r) = t_1^{***}(v_H, \mathbf{v}_{-1}^r) = v_L$ and $x_1^{***}(v_L, \mathbf{v}_{-1}^r) = x_1^{***}(v_H, \mathbf{v}_{-1}^r) = 1$, then she receives expected profits

$$\mathbb{E}\left[\Pi(\gamma(\mathbf{v})^{***})\right] = \pi_n\left[n_H(v_L-c)-I\right] \tag{A.4}$$

and demand state (n_L, v_H) does not get financing. If the entrepreneur chooses $t_1^{**}(v_L, \mathbf{v}_{-1}^r) = x_1^{**}(v_L, \mathbf{v}_{-1}^r) = 0$, $t_1^{**}(v_H, \mathbf{v}_{-1}^r) = v_H$ and $x_1^{**}(v_H, \mathbf{v}_{-1}^r) = 1$, then she receives

$$\mathbb{E}\left[\Pi(\gamma^{**}(\mathbf{v}))\right] = \pi_n\pi_v\left[n_H(v_H-c)-I\right] + (1-\pi_n)\pi_v\left[n_L(v_H-c)-I\right] \tag{A.5}$$

and demand state (n_H, v_L) does not get financing. To finance all demand states and implement first-best allocations, the entrepreneur may use the transfer schedule

$$t_1^*(v_1^r, \mathbf{v}_{-1}^r) = \begin{cases} v_L & \text{if } (v_1^r = v_L \text{ or } v_1^r = v_H) \text{ and } n_H \text{ consumers report } v_1^r > 0 \\ v_H & \text{if } (v_1^r = v_H) \text{ and } n_L \text{ consumers report } v_H \end{cases} \tag{A.6}$$

and production decisions

$$x_1^*(v_1^r, \mathbf{v}_{-1}^r) = 1 \text{ if } n_L \text{ consumers report } v_H \text{ or } n_H \text{ consumers report } v_1^r > 0, \tag{A.7}$$

which yields an expected profit of

$$\mathbb{E}\left[\Pi(\gamma^*(\mathbf{v}))\right] = \pi_n\left[n_H(v_L-c)-I\right] + (1-\pi_n)\pi_v\left[n_L(v_H-c)-I\right]. \tag{A.8}$$

Clearly, (A.8) always dominates (A.4) but strictly dominates (A.5) only if

$$(1-\pi_v)\left[n_H(v_L-c)-I\right] > \pi_v n_H\left(v_H-v_L\right). \tag{A.9}$$

The entrepreneur hence prefers to charge the high price and only produce for consumers with high valuations if this condition is violated. If this condition is satisfied, on the other hand, then the entrepreneur optimally implements first-best allocations.

To conclude the proof, observe that consumers only receive the information rent $v_H - v_L$ in state (n_H, v_H) and if the entrepreneur chooses the mechanism that implements first-best allocations, while consumers with valuation v_L never receive any surplus. □

B Appendix to 'Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets'

B.1 Proofs

Proof of Lemma 4. The proof of the lemma is an application of Equation (2.2) in Barndorff-Nielsen et al. (1982). □

Proof of Theorem 1. First, note that the characteristic function in Lemma 4 yields the first moment μ_r of the returns as

$$
\begin{aligned}
\mathbb{E}_t\left(r^{b,s}_{(t:t+\tau)}\right) &= (-i)\frac{\partial}{\partial u}\varphi_{r^{b,s}_{(t:t+\tau)}}(u)\bigg|_{u=0} \\
&= \delta^{b,s}_t e^{iu\delta^{b,s}_t} m_\tau\left(iu\mu^s_t - \frac{1}{2}u^2(\sigma^s_t)^2\right) \\
&\quad + e^{iu\delta^{b,s}_t} m'_\tau\left(iu\mu^s_t - \frac{1}{2}u^2(\sigma^s_t)^2\right)\left(\mu^s_t + iu(\sigma^s_t)^2\right)\bigg|_{u=0} \\
&= \delta^{b,s}_t + \mathbb{E}_t(\tau)\mu^s_t,
\end{aligned} \tag{B.1}
$$

since $m_\tau(0) = 1$ and $m'_\tau(0) = \mathbb{E}_t(\tau)$ by definition of the moment-generating function.

In the spirit of Arditti (1967) and Scott and Horvath (1980), we express the expected utility of the arbitrageur by a Taylor expansion which results in a function of the higher-order moments of the return distribution. A Taylor expansion of a general utility function $U_\gamma(r)$ around the mean μ_r yields

$$
U_\gamma\left(r^{b,s}_{(t:t+\tau)}\right) = \sum_{k=0}^{\infty}\frac{U^{(k)}_\gamma(\mu_r)}{k!}\left(r^{b,s}_{(t:t+\tau)} - \mu_r\right)^k, \tag{B.2}
$$

where $U_\gamma^{(k)}(\mu_r) := \frac{\partial^k}{\partial \mu_r^k} U_\gamma(\mu_r)$. Then, taking expectations yields

$$\mathbb{E}_t\left(U_\gamma\left(r_{(t:t+\tau)}^{b,s}\right)\right) = U_\gamma(\mu_r) + \sum_{k=2}^{\infty} \frac{U_\gamma^{(k)}(\mu_r)}{k!} \mathbb{E}_t\left(\left(r_{(t:t+\tau)}^{b,s} - \mu_r\right)^k\right). \tag{B.3}$$

Following Markowitz (1952), we next consider a first-order Taylor expansion for the CE. We thus implicitly assume that the risk premium, $\mu_r - CE$, is small and that higher-order moments vanish:

$$\mathbb{E}_t\left(U_\gamma\left(r_{(t:t+\tau)}^{b,s}\right)\right) = U_\gamma(CE) = U_\gamma(\mu_r) + U_\gamma'(\mu_r)(CE - \mu_r). \tag{B.4}$$

Moreover, the first-order Taylor expansion provides a convenient closed-form approximation of the certainty equivalent which is linear in the moments of the return distribution. We obtain the equation in the theorem by equating (B.3) and (B.4), plugging in (B.1), and solving for CE. □

Proof of Lemma 5. The proof follows directly from applying Theorem 1 together with the derivatives of the isoelastic utility function which yields

$$d_t^s - \frac{1}{2}\frac{\gamma}{d_t^s}(\sigma_t^s)^2 \mathbb{E}_t(\tau) - \frac{1}{8}\frac{\gamma(\gamma+1)(\gamma+2)}{(d_t^s)^3}(\sigma_t^s)^4 \mathbb{E}_t\left(\tau^2\right) = 0. \tag{B.5}$$

Details regarding the moment-generating function of the returns are provided in Appendix B.4. Then, by Descartes' rule of signs there is exactly one positive real root to the polynomial

$$(d_t^s)^4 - \frac{1}{2}\gamma(\sigma_t^s)^2 \mathbb{E}_t(\tau)(d_t^s)^2 - \frac{1}{8}\gamma(\gamma+1)(\gamma+2)(\sigma_t^s)^4 \mathbb{E}_t\left(\tau^2\right) = 0. \tag{B.6}$$

All four solutions of the quartic polynomial are given by

$$d_t^s = \pm\frac{1}{\sqrt{2}}\sqrt{\frac{\gamma}{2}(\sigma_t^s)^2 \mathbb{E}_t(\tau) \pm \sqrt{\frac{\gamma^2}{4}(\sigma_t^s)^4 \mathbb{E}_t(\tau)^2 + \frac{\gamma(\gamma+1)(\gamma+2)}{2}(\sigma_t^s)^4 \mathbb{E}_t(\tau^2)}}. \tag{B.7}$$

However, since

$$\frac{\gamma}{2}(\sigma_t^s)^2 \mathbb{E}_t(\tau) < \sqrt{\frac{\gamma^2}{4}(\sigma_t^s)^4 \mathbb{E}_t(\tau)^2 + \frac{\gamma(\gamma+1)(\gamma+2)}{2}(\sigma_t^s)^4 \mathbb{E}_t(\tau^2)} \tag{B.8}$$

holds for all $\gamma > 0$, $\sigma_t^s > 0$ and $\mathbb{E}_t(\tau^2) > 0$, the unique positive real root is given by the expression in the lemma. □

Proof of Lemma 6. The Taylor representation of $U_\gamma(\tilde{r})$ yields for $\rho^* := \log\left(\frac{1+\rho^{b,A}(q)}{1-\rho^{s,B}(q)}\right)$:

$$\begin{aligned}\mathbb{E}_t\left(U_\gamma(\tilde{r})\right) = &\ \delta_t^{b,s} + \mathbb{E}_t(\tau)\mu_t^s - \rho^* \\ &+ \sum_{k=2}^{\infty} \frac{U_\gamma^{(k)}\left(\delta_t^{b,s} + \mathbb{E}_t(\tau)\mu_t^s - \rho^*\right)}{k! U_\gamma'\left(\delta_t^{b,s} + \mathbb{E}_t(\tau)\mu_t^s - \rho^*\right)} \mathbb{E}_t\left(\left(r_{(t:t+\tau)}^{b,s} - \rho^* - \delta_t^{b,s} - \mathbb{E}_t(\tau)\mu_t^s\right)^k\right).\end{aligned} \tag{B.9}$$

Let d_t^s be the arbitrage boundary (in absence of transaction costs) as defined in Equation (2.8). Then, $d_t^s + \ln\left(\frac{1+\rho_t^{b,A}(q)}{1-\rho_t^{s,B}(q)}\right)$ is a root of the function

$$\begin{aligned}\tilde{F}(d) :=& d + \mathbb{E}_t(\tau)\mu_t^s - \rho^* \\ &+ \sum_{k=2}^{\infty} \frac{U_\gamma^{(k)}\left(d + \mathbb{E}_t(\tau)\mu_t^s - \rho^*\right)}{k! U_\gamma'\left(d + \mathbb{E}_t(\tau)\mu_t^s - \rho^*\right)} \mathbb{E}_t\left(\left(r_{(t:t+\tau)}^{b,s} - \rho^* - d - \mathbb{E}_t(\tau)\mu_t^s\right)^k\right).\end{aligned} \tag{B.10}$$

Therefore, $\mathbb{E}_t\left(U_\gamma(\tilde{r})\right)$ is positive if and only if

$$\delta_t^{b,s} > d_t^s + \ln\left(\frac{1+\rho_t^{b,A}(q)}{1-\rho_t^{s,B}(q)}\right). \tag{B.11}$$

□

Proof of Lemma 7. The proof directly follows from Lemma 6 and Theorem 1. □

Proof of Lemma 8. We cast the arbitrageur's optimization problem in terms of the Lagrangian

$$\begin{aligned}\mathcal{L}(q,f;\xi) =& B_t^s(1-\rho^{s,B}(q))q + A_t^b(1+\rho^{b,A}(q+f))(q+f) \\ &- \xi\left(d_t^s(f) - \delta_t^{b,s} + \log\left(1+\rho^{b,A}(q)\right) - \log\left(1-\rho^{s,B}(q)\right)\right)\end{aligned} \tag{B.12}$$

and observe that the corresponding Karush-Kuhn-Tucker (KKT) conditions imply

$$\begin{aligned} q = 0 \quad \vee \quad & B_t^s \Big((1 - \rho^{s,B}(q)) - \rho^{s,B'}(q) q \Big) \\ & - A_t^b \Big((1 + \rho^{b,A}(q+f)) + \rho^{b,A'}(q+f)(q+f) \Big) \\ & - \xi \left(\frac{\rho^{b,A'}(q+f)}{1+\rho^{b,A}(q+f)} - \frac{\rho^{s,B'}(q)}{1+\rho^{s,B}(q)} \right) = 0 \qquad \text{(B.13)} \\ f = 0 \quad \vee \quad & - A_t^b \Big((1 + \rho^{b,A}(q+f)) + \rho^{b,A'}(q+f)(q+f) \Big) \\ & - \xi \left(\frac{d}{df} d_t^s(f) + \frac{\rho^{b,A'}(q+f)}{1+\rho^{b,A}(q+f)} \right) = 0 \qquad \text{(B.14)} \\ \xi = 0 \quad \vee \quad & d_t^s(f) - \delta_t^{b,s} \\ & + \log \big(1 + \rho^{b,A}(q+f) \big) - \log \big(1 - \rho^{s,B}(q) \big) = 0. \qquad \text{(B.15)} \end{aligned}$$

We first consider the case of $\xi = 0$. Conditions (B.13) and (B.14) now become

$$\begin{aligned} q = 0 \quad \vee \quad & B_t^s \Big((1 - \rho^{s,B}(q)) - \rho^{s,B'}(q) q \Big) \\ & - A_t^b \Big((1 + \rho^{b,A}(q+f)) + \rho^{b,A'}(q+f)(q+f) \Big) = 0 \qquad \text{(B.16)} \\ f = 0 \quad \vee \quad & - A_t^b \Big((1 + \rho^{b,A}(q+f)) + \rho^{b,A'}(q+f)(q+f) \Big) = 0, \qquad \text{(B.17)} \end{aligned}$$

which only holds if

$$1 + \rho^{b,A}(q+f) = -\rho^{b,A'}(q+f)(q+f). \qquad \text{(B.18)}$$

Since $\rho^{b,A'}(q+f) > 0$ by Assumption 4, this cannot be the case for any $q > 0$ or $f > 0$. Also note that $\xi = q = f = 0$ implies a contradiction. Therefore, constraint given in Equation (2.16) cannot be slack at the optimum and there does not exist a candidate solution for $\xi = 0$.

Next, we turn to the analysis of $\xi > 0$. The simple case of $q = 0$ does not deliver any positive returns and it does not make sense for the arbitrageur to pay any fee $f > 0$. If anything, the arbitrageur would prefer not to trade at all, that is, $q = f = 0$. We are left with the two interesting cases of $q > 0$.

For $f = 0$, the KKT conditions give the candidate solution $\{q_1, f_1, \xi_1\}$ as solutions to the system of equations

$$B_t^s\left((1-\rho^{s,B}(q_1))-\rho^{s,B'}(q_1)q_1\right)-A_t^b\left((1+\rho^{b,A}(q_1))+\rho^{b,A'}(q_1)(q_1)\right)$$
$$-\xi_1\left(\frac{\rho^{b,A'}(q_1)}{1+\rho^{b,A}(q_1)}-\frac{\rho^{s,B'}(q_1)}{1+\rho^{s,B}(q_1)}\right)=0 \quad \text{(B.19)}$$
$$d_t^s(f_1)-\delta_t^{b,s}+\log\left(1+\rho^{b,A}(q_1)\right)-\log\left(1-\rho^{s,B}(q_1)\right)=0 \quad \text{(B.20)}$$
$$f_1=0. \quad \text{(B.21)}$$

For $f>0$, we can get the candidate solution $\{q_2, f_2, \xi_2\}$ as solutions to

$$B_t^s\left((1-\rho^{s,B}(q_2))-\rho^{s,B'}(q_2)q_2\right)$$
$$-A_t^b\left((1+\rho^{b,A}(q_2+f_2))+\rho^{b,A'}(q_2+f)(q_2+f_2)\right)$$
$$-\xi\left(\frac{\rho^{b,A'}(q_2+f_2)}{1+\rho^{b,A}(q_2+f_2)}-\frac{\rho^{s,B'}(q_2)}{1+\rho^{s,B}(q_2)}\right)=0 \quad \text{(B.22)}$$
$$-A_t^b\left((1+\rho^{b,A}(q_2+f_2))+\rho^{b,A'}(q_2+f_2)(q_2+f_2)\right)$$
$$-\xi\left(\frac{d}{df}d_t^s(f_2)+\frac{\rho^{b,A'}(q_2+f_2)}{1+\rho^{b,A}(q_2+f_2)}\right)=0 \quad \text{(B.23)}$$
$$d_t^s(f_2)-\delta_t^{b,s}+\log\left(1+\rho^{b,A}(q_2+f_2)\right)-\log\left(1-\rho^{s,B}(q_2)\right)=0. \quad \text{(B.24)}$$

However, combining (B.22) and (B.23) shows that the solutions are only admissible if

$$\xi=\frac{B_t^s\left((1-\rho^{s,B}(q_2))-\rho^{s,B'}(q_2)q_2\right)}{\frac{d}{df}d_t^s(f_2)-\frac{\rho^{s,B'}(q_2)}{1+\rho^{s,B}(q_2)}}>0. \quad \text{(B.25)}$$

Equation (B.25) now provides us with necessary conditions for a solution to the problem that entails a strictly positive settlement fee. Namely, $q_2>0$, $f_2>0$ $\xi_2>0$ can only be solution if one of the following two conditions holds

(i) $-\frac{d}{df}d_t^s(f_2)>\frac{\rho^{s,B'}(q_2)}{1-\rho^{s,B}(q_2)}$ and $1-\rho^{s,B}(q_2)>\rho^{s,B'}(q_2)q_2$

(ii) $-\frac{d}{df}d_t^s(f_2)<\frac{\rho^{s,B'}(q_2)}{1-\rho^{s,B}(q_2)}$ and $1-\rho^{s,B}(q_2)<\rho^{s,B'}(q_2)q_2$.

However, condition (ii) cannot hold at the maximum since $1-\rho^{s,B}(q_2)<\rho^{s,B'}(q_2)q_2$ means that the trading quantity is such that the marginal price impact exceeds the average price impact. In this case, the arbitrageur would reduce the trading quantity to raise her total return. Consequently, (i) remains as the necessary condition for a candidate solution with a positive settlement fee which completes the proof. □

B.2 Latency Distribution under Stochastic Volatility

We can relax the assumption that σ_t^s is constant over the interval $[t, t+\tau]$ by allowing σ_t^s to vary over time. More specifically, let $\sigma_t^s : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ with $\theta(\tau) := \int_t^{t+\tau} (\sigma_k^s)^2 \, dk < \infty \quad \forall \tau$, that is, the volatility of the sell-side market follows a (deterministic) path with bounded integrated variance. Assuming $\mu_t^s = 0$, we can then rewrite the log returns of the arbitrageur for given latency τ as

$$r_{(t:t+\tau)}^{b,s} = \delta_t^{b,s} + \int_t^{t+\tau} \sigma_k^s dW_k^s. \tag{B.26}$$

The integral above corresponds to a Gaussian process with independent increments. More specifically, we get

$$\mathbb{E}_t \left(\left(r_{(t:t+\tau)}^{b,s} - \delta_t^{b,s} \right)^2 \right) = \theta(\tau) - \theta(0) = \mathbb{E}_t \left(W_{\theta(\tau)}^s - W_{\theta(0)}^s \right). \tag{B.27}$$

In other words, the time-changed Brownian motion $W_{\theta(t)}^s$ has the same distribution as the log returns given in Equation (B.26) (e.g., Durrett, 1984; Barndorff-Nielsen et al., 2002). We can thus rewrite the return process as

$$r_{(t:t+\tau)}^{b,s} = \delta_t^{b,s} + \int_t^{t+\theta(\tau)} dW_k^s, \tag{B.28}$$

The implications of Lemma 4 still hold, but we need to compute the moment-generating function of the transformed latency $m_{\theta(\tau)}(u)$, which depends on the latency distribution and the dynamics of the volatility process. First, note that, as $\theta(\tau)$ is strictly increasing, the probability integral transformation yields the distribution of $\tau(\theta)$,

$$\mathbb{P}_t \left(\theta(\tau) = y \right) = \mathbb{P}_t \left(\tau = \theta^{-1}(y) \right) \quad \forall y > 0. \tag{B.29}$$

Finally, the distribution of $\theta(\tau)$ is fully described via its characteristic function which is of the form

$$\varphi_{\theta(\tau)}(u) = \mathbb{E}_t\left(e^{i\theta(\tau)u}\right) = \frac{1}{2\pi}\int_0^{\infty}\int_{-\infty}^{\infty}\varphi_\tau(s)\, e^{-is\tau} ds e^{i\theta(\tau)u} d\tau. \tag{B.30}$$

Lévys characterization allows to extend these ideas to more general non-deterministic integrands and to stochastic time-changes. Although Equation (B.30) allows to derive theoretical arbitrage bounds based on Theorem 1 for every continuous local martingale, we restrict our analysis to analytically more tractable and intuitive dynamics of the price process and the associated settlement latency.

B.3 Return Distribution for Exponentially-Distributed Latency

To provide an illustrative example, we parameterize the probability distribution of the stochastic latency as an exponential distribution with locally-constant scale parameter $\lambda_t := \lambda(\mathcal{I}_t)$. The probability density function of the latency is then given by

$$\pi_t(\tau) = \lambda_t e^{-\lambda_t \tau}, \tag{B.31}$$

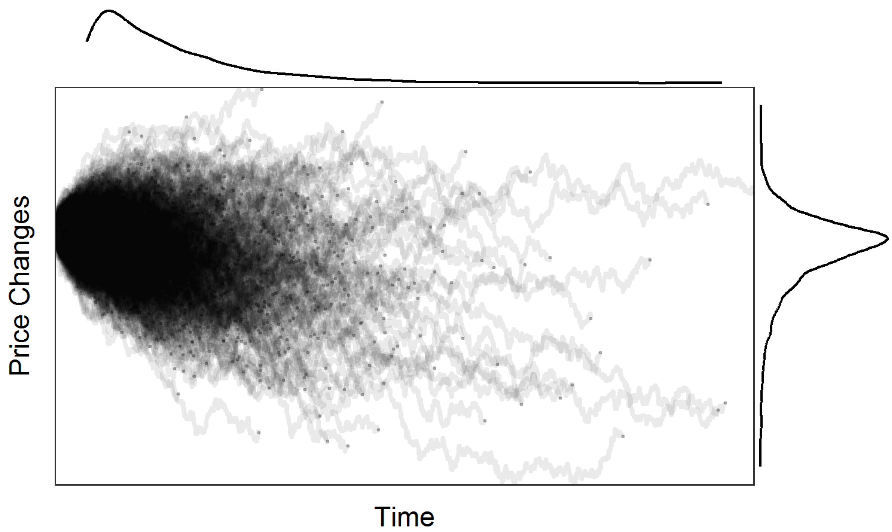
with conditional mean $\mathbb{E}_t(\tau) = \lambda_t^{-1}$ and conditional variance $\mathbb{V}_t(\tau) = \lambda_t^{-2}$. The moment-generating function of the exponential distribution is $m_\tau(u) = \left(1 - \lambda_t^{-1}u\right)^{-1}$. Thus, Lemma 4 yields

$$\varphi_{r^{b,s}_{(t:t+\tau)}}(u) = \frac{e^{iu\delta_t^{b,s}}}{1 - i\frac{\mu_t^s}{\lambda_t}u + \frac{(\sigma_t^s)^2}{2\lambda_t}u^2}, \tag{B.32}$$

which corresponds to the characteristic function of an asymmetric Laplace distribution with $\mathbb{E}_t\left(r^{b,s}_{(t:t+\tau)}\right) = \delta_t^{b,s} + \frac{\mu_t^s}{\lambda_t}$ and $\mathbb{V}_t\left(r^{b,s}_{(t:t+\tau)}\right) = \frac{1}{\lambda_t}\left((\mu_t^s)^2 + (\sigma_t^s)^2\right)$ (e.g., Kotz et al., 2012). Without a drift ($\mu_t^s = 0$), the distribution collapses to a symmetric Laplace distribution with location parameter $\delta_t^{b,s}$, scale parameter $\frac{\sigma_t^s}{\sqrt{2\lambda_t}}$, and corresponding probability density function

$$\pi_t\left(r^{b,s}_{(t:t+\tau)}\right) = \frac{\sqrt{2\lambda_t}}{2\sigma_t^s}\exp\left(-\frac{\sqrt{2\lambda_t}}{\sigma_t^s}\left|r^{b,s}_{(t:t+\tau)} - \delta_t^{b,s}\right|\right), \tag{B.33}$$

Figure B.1: Return Distribution under Exponentially-Distributed Latency



Notes: This figure illustrates the impact of stochastic latency (horizontal axis) on the distribution of returns (vertical axis) if log prices follow a Brownian motion and if latencies are exponentially distributed. The individual paths correspond to sample draws of the price process and the dots correspond to the terminal value of the stopped Wiener process. The marginal distribution at the top corresponds to the sampled latencies. The marginal distribution on the right-hand side corresponds to the sampled distribution of returns which converges in the limit to a Laplace distribution. The figure below shows the resulting distributions for a price process with negative drift $\mu_t^s < 0$.

with $\mathbb{E}_t\left(r_{(t:t+\tau)}^{b,s}\right) = \delta_t^{b,s}$ and $\mathbb{V}_t\left(r_{(t:t+\tau)}^{b,s}\right) = \left(\sigma_t^s\right)^2 \mathbb{E}_t\left(\tau\right)$. Hence, not surprisingly, in the absence of a drift in the underlying Brownian motion, the (conditionally) expected return implied by the arbitrage strategy is equal to the instantaneous return $\delta_t^{b,s} = b_t^s - a_t^b$. The (conditional) variance equals the (locally constant) spot variance on market s, $\left(\sigma_t^s\right)^2$, scaled by the (conditional) expected waiting time until the settlement of the transaction, λ_t^{-1}. Hence, the higher the volatility on the sell-side market or the longer the expected waiting time until the transfer is settled, the higher is the risk of extreme adverse price movements.

Figure B.1 provides a graphical illustration of the resulting distribution. The plot shows simulated draws from a Brownian motion stopped at randomly sampled waiting times. The marginal distribution at the top of the figure illustrates the exponential distribution of the waiting times. The marginal distribution on the right-hand side shows the resulting sampling distribution of the price process which converges in the limit to a Laplace distribution. The figure shows the resulting asymmetric Laplace distribution for a price process with a negative drift, whereas a price process without drift would yield a symmetric Laplace distribution.

B.4 Arbitrage Bound under Constant Absolute Risk Aversion

We provide a further application of our main result to the case of the commonly-used utility function with constant absolute risk aversion (CARA). Again, we ignore the impact of higher order moments above the fourth degree of the Taylor representation in Equation (2.7). These assumptions yield an analytically tractable formulation of the arbitrage bound.

Lemma 9. *If, in addition to Assumptions 1 and 2, the arbitrageur has an exponential utility function* $U_\gamma(r) := \frac{1-e^{-\gamma(1+r)}}{\gamma}$ *with risk aversion* $\gamma > 0$*, then the arbitrage boundary is*

$$\begin{aligned} d_t^s = &- \mathbb{E}_t(\tau)\,\mu_t^s + \frac{\gamma}{2}\left(\mathbb{V}_t(\tau)\left(\mu_t^s\right)^2 + \left(\sigma_t^s\right)^2 \mathbb{E}_t(\tau)\right) \\ &- \frac{\gamma^2}{6}\left(3\mu_t^s\left(\sigma_t^s\right)^2 \mathbb{V}_t(\tau) + \left(\mu_t^s\right)^3 \mathbb{E}_t\left(\left(\tau - \mathbb{E}_t(\tau)\right)^3\right)\right) \\ &+ \frac{\gamma^3}{24}\left(\left(\mu_t^s\right)^4 \mathbb{E}_t\left(\left(\tau - \mathbb{E}_t(\tau)\right)^4\right) + 6\left(\sigma_t^s\right)^2\left(\mu_t^s\right)^2\left(\mathbb{E}(\tau)^3 + \mathbb{E}_t\left(\tau^3\right) - 2\mathbb{E}_t(\tau)^2\right)\right) \\ &+ \frac{\gamma^3}{8}\mathbb{E}_t\left(\tau^2\right)\left(\sigma_t^s\right)^4 . \end{aligned} \tag{B.34}$$

Proof. For the exponential utility, we have $U^{(k)}(r)/U'(r) = (-\gamma)^{k-1}$ for $k \geq 1$. Therefore, from Theorem 1 we have

$$\begin{aligned} CE = \delta_t^{b,s} + \mathbb{E}_t(\tau)\,\mu_t^s - \frac{\gamma}{2}\mu_{r^{b,s}_{(t:t+\tau)}}(2) \\ + \frac{\gamma^2}{6}\mu_{r^{b,s}_{(t:t+\tau)}}(3) - \frac{\gamma^3}{24}\mu_{r^{b,s}_{(t:t+\tau)}}(4) + \mathcal{O}(r)\,, \end{aligned} \tag{B.35}$$

where $\mu_{r^{b,s}_{(t:t+\tau)}}(k) := \mathbb{E}_t\left(\left(r^{b,s}_{(t:t+\tau)} - \delta_t^{b,s} - \mathbb{E}_t(\tau)\,\mu_t^s\right)^k\right)$ is the k-th order central moment of the returns and $\mathcal{O}(r)$ corresponds to the Taylor approximation error which we neglect subsequently. Recognizing that by definition $m_{r^{b,s}_{(t:t+\tau)}}(iu) = \varphi_{r^{b,s}_{(t:t+\tau)}}(u)$, we can derive the moment-generating function of the returns given by

$$m_{r^{b,s}_{(t:t+\tau)}}(u) = e^{u\delta_t^{b,s}} m_\tau\left(u\mu_t^s + \frac{1}{2}u^2(\sigma_t^s)^2\right). \tag{B.36}$$

The central moment-generating function is defined as

$$\begin{aligned} C_{r^{b,s}_{(t:t+\tau)}}(u) &= \mathbb{E}_t\left(\exp\left(u\left(r_{(t:t+\tau)} - \mathbb{E}_t(r^{b,s}_{(t:t+\tau)})\right)\right)\right) \\ &= \exp\left(-u\mathbb{E}_t(r^{b,s}_{(t:t+\tau)})\right) m_{r^{b,s}_{(t:t+\tau)}}(u)\,. \end{aligned} \tag{B.37}$$

Thus, we have

$$\begin{aligned} \mu_{r^{b,s}_{(t:t+\tau)}}(k) &= \frac{\partial^k}{\partial u^k} C_{r^{b,s}_{(t:t+\tau)}}(u)\bigg|_{u=0} \\ &= \frac{\partial^k}{\partial u^k}\exp\left(-\mathbb{E}_t\left(\tau\right)\mu^s_t u\right) m_\tau\left(u\mu^s_t + \frac{1}{2}u^2\left(\sigma^s_t\right)^2\right)\bigg|_{u=0}. \end{aligned} \tag{B.38}$$

Basic calculus then yields

$$\mu_{r^{b,s}_{(t:t+\tau)}}(2) = \mathbb{V}_t\left(\tau\right)\left(\mu^s_t\right)^2 + \left(\sigma^s_t\right)^2\mathbb{E}_t\left(\tau\right) \tag{B.39}$$

$$\mu_{r^{b,s}_{(t:t+\tau)}}(3) = 3\mu^s_t\left(\sigma^s_t\right)^2\mathbb{V}_t\left(\tau\right) + \left(\mu^s_t\right)^3\mathbb{E}_t\left(\left(\tau - \mathbb{E}_t\left(\tau\right)\right)^3\right) \tag{B.40}$$

$$\begin{aligned} \mu_{r^{b,s}_{(t:t+\tau)}}(4) &= \left(\mu^s_t\right)^4\mathbb{E}_t\left(\left(\tau - \mathbb{E}_t\left(\tau\right)\right)^4\right) + 3\mathbb{E}_t\left(\tau^2\right)\left(\sigma^s_t\right)^4 \\ &\quad + 6\left(\sigma^s_t\right)^2\left(\mu^s_t\right)^2\left(\mathbb{E}_t\left(\tau\right)^3 + \mathbb{E}_t\left(\tau^3\right) - 2\mathbb{E}_t\left(\tau\right)\mathbb{E}_t\left(\tau^2\right)\right). \end{aligned} \tag{B.41}$$

Then, we plug in equations (B.39)-(B.41) into (B.35). Finally, recognizing that the arbitrageur exploits price differences if and only if $CE > 0$, we can solve for the minimum instantaneous price differences $\delta^{b,s}_t$ which completes the proof. □

In the absence of a drift ($\mu^s_t = 0$), the arbitrage boundary of Lemma 9 further simplifies to

$$d^s_t = \frac{\gamma}{2}(\sigma^s_t)^2\mathbb{E}_t\left(\tau\right) + \frac{\gamma^3}{8}(\sigma^s_t)^4\left(\mathbb{V}_t\left(\tau\right) + \mathbb{E}_t\left(\tau\right)^2\right). \tag{B.42}$$

Just like in the case of CRRA, the arbitrage boundary d^s_t positively depends on (i) the arbitrageur's risk aversion, (ii) the local volatility on the sell-side market s, (iii) the expected waiting time until settlement, and (iv) the variance of the waiting time, $\mathbb{V}_t\left(\tau\right)$.

B.5 No-Arbitrage Implied Relative Risk Aversion

We compute the implied relative risk aversion $\hat{\gamma}^{b,s}_t$ such that all observed price differences of exchange pair $\{b, s\}$ at time t are located within the implied limits to arbitrage.

The interpretation of $\hat{\gamma}_t^{b,s}$ is straightforward: if the risk aversion of an arbitrageur is below $\hat{\gamma}_t^{b,s}$, it would be rational to trade. We compute $\hat{\gamma}_t^{b,s}$ according to the following lemma.

Lemma 10. *Define $\hat{\gamma}_t^{b,s}$ as the root of the cubic polynomial*

$$\left(\tilde{\delta}_t^{b,s}\right)^4 - \frac{1}{8}\left(\hat{\sigma}_t^s\right)^4 c_2 \left(\hat{\gamma}_t^{b,s}\right)^3 - \frac{3}{8}\left(\hat{\sigma}_t^s\right)^4 c_2 \left(\hat{\gamma}_t^{b,s}\right)^2 - \frac{1}{2}\left(\hat{\sigma}_t^s\right)^2 \left(c_1 \left(\tilde{\delta}_t^{b,s}\right)^2 + \frac{1}{2}\left(\hat{\sigma}_t^s\right)^2 c_2\right)\hat{\gamma}_t^{b,s} = 0, \tag{B.43}$$

where, analogously to Equations (2.27) *and* (2.28), $c_1 = \hat{\mathbb{E}}_t(\tau) + \hat{\mathbb{E}}(\tau_B) \cdot (B^s - 1)$ *and* $c_2 = \hat{\mathbb{V}}_t(\tau) + \hat{\mathbb{V}}(\tau_B) \cdot (B^s - 1)^2 + \left(\hat{\mathbb{E}}(\tau_B) \cdot (B^s - 1) + \hat{\mathbb{E}}_t(\tau)\right)^2$. *Then, price differences (adjusted for transaction costs) $\tilde{\delta}_t^{b,s}$ constitute a (statistical) arbitrage opportunity for an arbitrageur with risk aversion γ only if $\gamma < \hat{\gamma}_t^{b,s}$.*

Proof. The proof follows directly from applying Theorem 1 together with the derivatives of the utility function which yields

$$d_t^s - \frac{1}{2}\frac{\gamma}{d_t^s}(\sigma_t^s)^2 \mathbb{E}_t(\tau) - \frac{1}{8}\frac{\gamma(\gamma+1)(\gamma+2)}{(d_t^s)^3}(\sigma_t^s)^4 \mathbb{E}_t\left(\tau^2\right) = 0. \tag{B.44}$$

Then, by Descartes' rule of signs there is exactly one positive real root to the polynomial

$$(d_t^s)^4 - \frac{1}{2}\gamma(\sigma_t^s)^2 \mathbb{E}_t(\tau)(d_t^s)^2 - \frac{1}{8}\gamma(\gamma+1)(\gamma+2)(\sigma_t^s)^4 \mathbb{E}_t\left(\tau^2\right) = 0. \tag{B.45}$$

By definition, d_t^s corresponds to the arbitrage boundary for a given risk aversion γ. The arbitrageur prefers to trade if observed price differences $\tilde{\delta}_t^s$ exceed the boundary. Therefore, rewriting Equation (B.45) in terms of γ and replacing d_t^s with $\tilde{\delta}_t^s$ yields a cubic polynomial in γ :

$$\left(\tilde{\delta}_t^{b,s}\right)^4 - \frac{1}{8}\left(\hat{\sigma}_t^s\right)^4 \mathbb{E}_t\left(\tau^2\right) \left(\hat{\gamma}_t^{b,s}\right)^3 - \frac{3}{8}\left(\hat{\sigma}_t^s\right)^4 \mathbb{E}_t\left(\tau^2\right) \left(\hat{\gamma}_t^{b,s}\right)^2 - \frac{1}{2}\left(\hat{\sigma}_t^s\right)^2 \left(\mathbb{E}_t(\tau) \left(\tilde{\delta}_t^{b,s}\right)^2 + \frac{1}{2}\left(\hat{\sigma}_t^s\right)^2 \mathbb{E}_t\left(\tau^2\right)\right)\hat{\gamma}_t^{b,s} = 0 \tag{B.46}$$

Replacing the (conditional) expected latencies with the values given by Equations (2.27) and (2.28) completes the proof. □

The exchange pair-specific implied risk aversion $\hat{\gamma}_t^{b,s}$ is defined in a way such that the observed price differences $\tilde{\delta}_t^{b,s}$, adjusted for transaction costs, coincide with the arbitrage bounds for an isoelastic utility function with risk aversion parameter $\hat{\gamma}_t^{b,s}$. As the arbitrage bounds monotonically increase with risk aversion, any value of $\gamma < \hat{\gamma}_t^{b,s}$ constitutes a trading opportunity for the arbitrageur. Conversely, $\gamma > \hat{\gamma}_t^{b,s}$ reflects that the observed price differences do not justify (unconstrained) trading because an arbitrageur with a higher risk aversion obtains higher (expected) utility by trading less or not at all. As the asset is traded on N markets, we define $\hat{\gamma}_t$ as the smallest risk aversion parameter for which all observed price differences fall within the implied arbitrage bounds, that is,

$$\hat{\gamma}_t := \max_{i,j \in \{1,\ldots,N\}} \hat{\gamma}_t^{i,j}. \tag{B.47}$$

C Appendix to 'Perceived Precautionary Savings Motives: Evidence from FinTech'

C.1 Supplementing Tables

Table C.1: Variable Definitions

Variable	Definition
Account Age	End of month date minus the date when the user completed the account opening procedure.
Big Ticket Expenditure	Indicator variable equal to one if the user has at least one transaction of more than 5,000 Euros in the given month.
Card Consumption	Total amount of electronic card consumption in the given month.
Cash Withdrawals	Total amount of cash withdrawals in the given month.
Consumption	Sum of *Card Consumption* and *Cash Withdrawals*.
Deposits	Total amount of available funds in a user's account at the end of a month.
Discretionary	Sum of users' monthly expenditures on *Entertainment*, *Shopping*, *Gastronomy*, and *Travel*.
Female	Indicator variable equal to one if the user is female.
Incoming Wire Transfers	Total amount of all SEPA credit transfers a user receives in the given month.
Inflows	Total amount of all incoming transactions a user receives in the given month.
Negative Deposits	Indicator variable equal to one if the user has a negative account balance in the given month.
Non-Discretionary	*Card Consumption* minus *Discretionary* spending.
Overdraft Available	Indicator variable equal to one if the user has access to a mobile overdraft in the given month.
Overdraft Amount	Maximum overdraft amount granted to the user by the bank in the given month.
Savings Rate	Lagged inflows minus total current outflows divided by lagged inflows.
Urban	Indicator variable equal to one if the user lives in a NUTS 3 region with a population of at least 500,000 people.
User Age	End of month date minus first day of user's birth year.

Table C.2: Survey Questions

Question	Possible Answers
Do you rate yourself as a risk-taking person or are you trying to avoid risks?	Scale from 0 (not willing to take risks) to 10 (very willing to take risks)
Would you say that you are a person who trusts others, or not?	Scale from 0 (I do not trust others) to 10 (I trust others fully)
When you make savings or investment decisions for yourself, which of the following statements describes you best?	1 - I take significant risks and want to generate high returns. 2 - I take above-average risks and want to achieve above-average returns. 3 - I take average risks and aim for average returns. 4 - I am not willing to take any financial risk and accept not to generate any returns.
Imagine, you get either 100 Euros immediately or a higher amount of money in a month. What is the lowest amount you would be willing to wait for a month?	1 - 101 Euros 2 - 103 Euros 3 - 108 Euros 4 - 117 Euros 5 - 125 Euros 6 - 133 Euros 7 - 150 Euros 8 - 167 Euros 9 - 183 Euros 10 - 200 Euros 11 - 233 Euros
How likely is it that you will face large, unexpected expenses over the next 12 months?	Scale from 0 (very unlikely) to 10 (very likely)
How likely is it that you will face large medical expenses for yourself or a family member over the next 12 months, including hospitalization and nursing care?	Scale from 0 (very unlikely) to 10 (very likely)
How likely are you to lose your job in the next 12 months?	Scale from 0 (very unlikely) to 10 (very likely)
How satisfied are you with your health at the moment?	Scale from 0 (not satisfied) to 10 (very satisfied)
What do you usually think of when saving?	1 - I usually save for very specific expenses, such as a vacation or a car. 2 - I usually save to have a small amount of money available for unexpected expenses. 3 - I do not save much or cannot save much. Whenever I put money aside, I do it without much thought. 4 - I am saving with the goal of building a small estate that I may pass on to my children, nephews, nieces, or other family members.
Suppose you have 100 Euros in your savings account and earn 10 percent interest per year. How high will be your balance after 2 years?	1 - Lower than 120 Euros 2 - 120 Euros 3 - Higher than 120 Euros
How high do you estimate your life expectancy?	Enter number

Table C.3: Characteristics of Survey Respondents

	Non-Respondents	Respondents	
	Mean	Mean	SD
User Age [Years]	33.78	38.37	9.93
Female [0/1=Yes]	0.22	0.12	0.41
Urban [0/1=Yes]	0.54	0.39	0.50
Account Age [Years]	1.56	1.77	0.86
Overdraft Available [0/1=Yes]	0.91	0.91	0.29
Overdraft Amount [Euro]	1,566.51	1,484.89	1,602.05
Consumption [Euro]	742.09	561.75	949.42
Inflows [Euro]	2,236.78	1,965.94	5,948.55
Consumption / Inflows [%]	48.33	44.86	44.89
Card Consumption [Euro]	506.49	379.95	736.64
Card Consumption / Inflows [%]	33.91	32.22	37.17
Cash Withdrawals [Euro]	223.92	175.96	400.55
Cash Withdrawals / Inflows [%]	13.53	12.04	19.56
Discretionary [Euro]	212.97	139.35	419.58
Non-Discretionary [Euro]	293.53	240.60	469.75
Discretionary / Non-Discretionary [%]	81.46	69.44	102.50
User Observations	565,423	37,734	603,157

Notes: This table provides descriptive statistics of characteristics for users who responded to the survey and those who did not respond. The last column reports the standard deviation of the corresponding characteristic across all users. We limit the sample to users that activate the overdraft facility in our main sample.

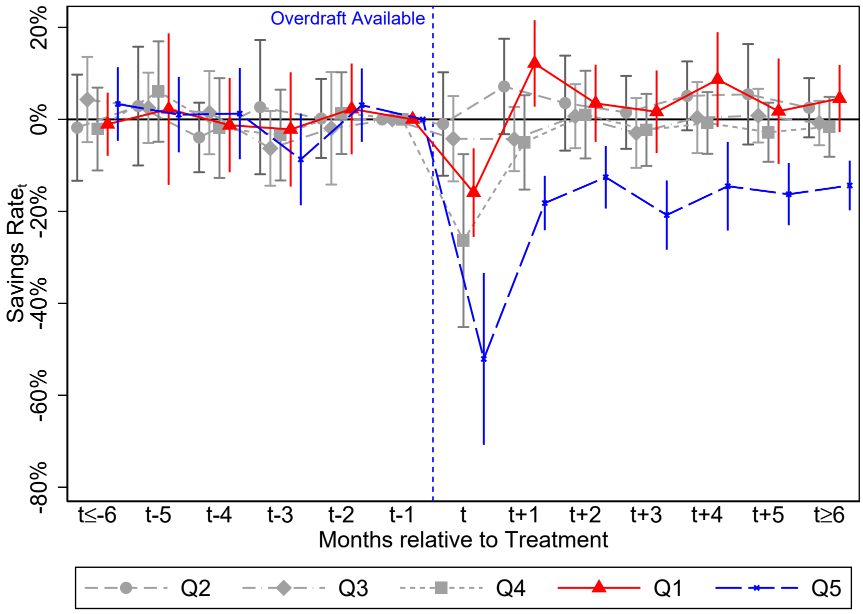
Table C.4: User Characteristics around Rounding Thresholds

	Rounded Up			Rounded Down			Difference in Means	
	Mean	SD	Median	Mean	SD	Median	Diff.	t-Stat.
User Age [Years]	32.32	9.34	29.91	33.02	10.12	30.37	0.70	1.13
Female [0/1=Yes]	0.25	0.43	0.00	0.24	0.43	0.00	-0.01	-0.35
Account Age [Years]	0.87	0.38	0.83	0.85	0.41	0.79	-0.01	-0.53
Inflows$_{t-3:t-1}$ [Euro]	1,405.64	1,530.10	1,101.67	1,458.92	1,454.29	1,069.67	53.28	0.56
Consumption$_{t-3:t-1}$ [Euro]	558.89	522.39	427.17	620.04	597.38	482.83	61.14*	1.70
Users	500			474			974	

Notes: This table reports non-parametric estimates for the RD treatment effect of a 250 Euros higher overdraft amount on several user characteristics. The dependent variables are the user's age, gender, and time since account opening at the treatment date. We only use polynomials of order 1 and 2 to avoid overfitting issues (Gelman and Imbens, 2018), apply weights from a triangular kernel because it is the mean squared error (MSE) minimizing choice (Cheng et al., 1997), and employ the MSE-optimal bandwidth selection procedure recommended by Calonico et al. (2014). We report both conventional and robust RD estimates (Calonico et al., 2014, 2019). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

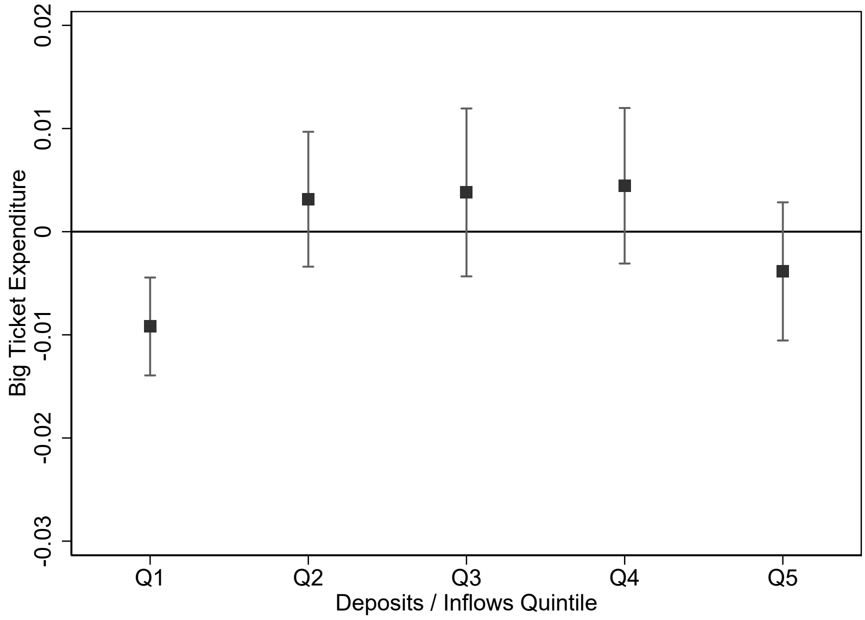
C.2 Supplementing Figures

Figure C.1: Savings Rate Pattern by Deposit-to-Income Quintile



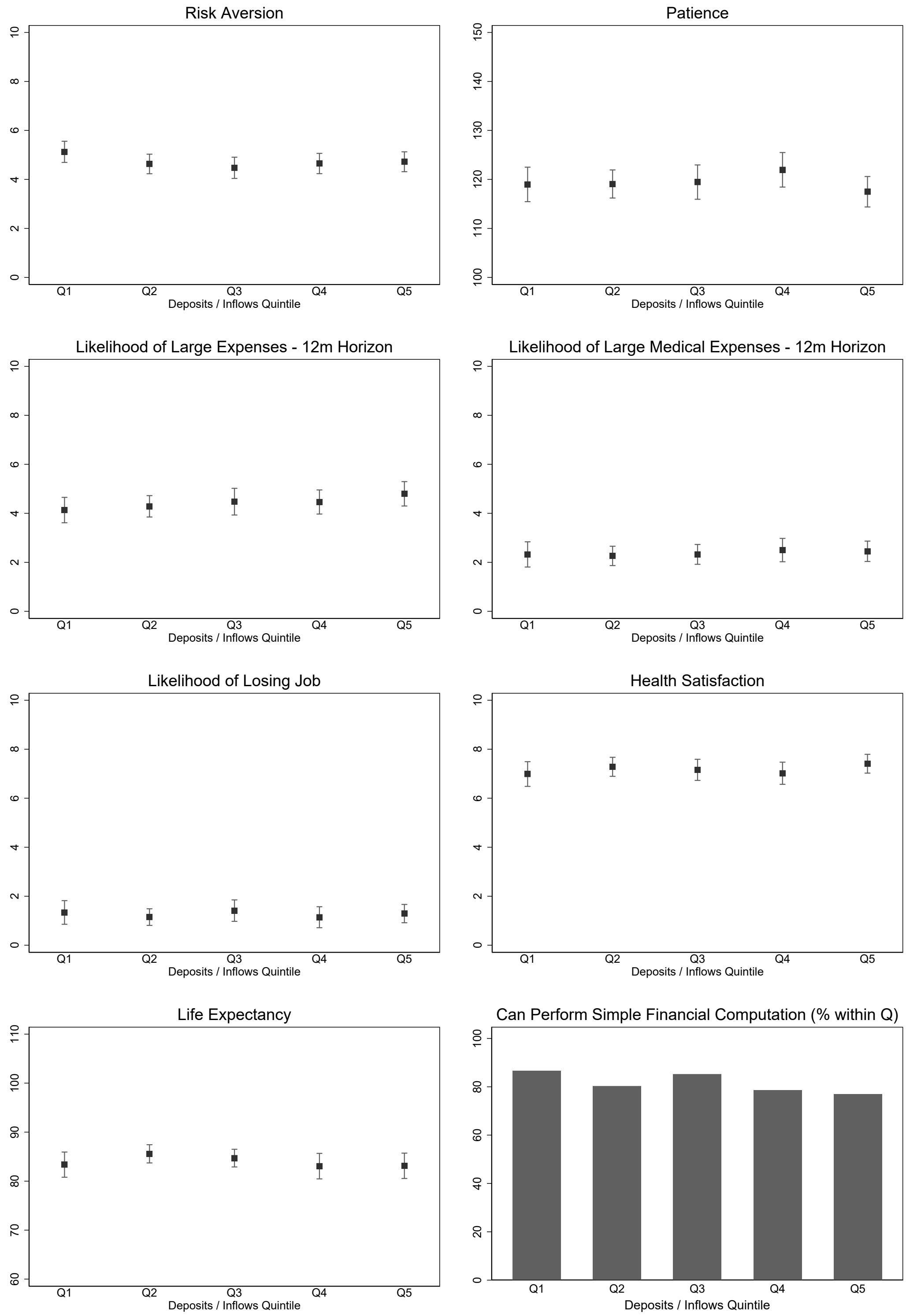
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the heterogeneous effect of mobile overdrafts on the savings behavior of users with different ex-ante liquidity. To generate this plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposits-to-inflows ratio in the month before treatment. We estimate model (1) from Table 3.2 but replace the *Overdraft Available* indicator with separate time dummies, which we further interact with our quintile indicators. Each time dummy marks a one-month period (except for event period $t-1$). Coefficients are normalized by subtracting the pre-treatment mean for each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

Figure C.2: Big Ticket Expenditure Response by Deposits-to-Inflows Quintile



Notes: This figure illustrates the cross-sectional heterogeneity in users' big ticket expenditure response after accessing the mobile overdraft. To generate this plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the underlying user characteristic. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS 2 and year-month level.

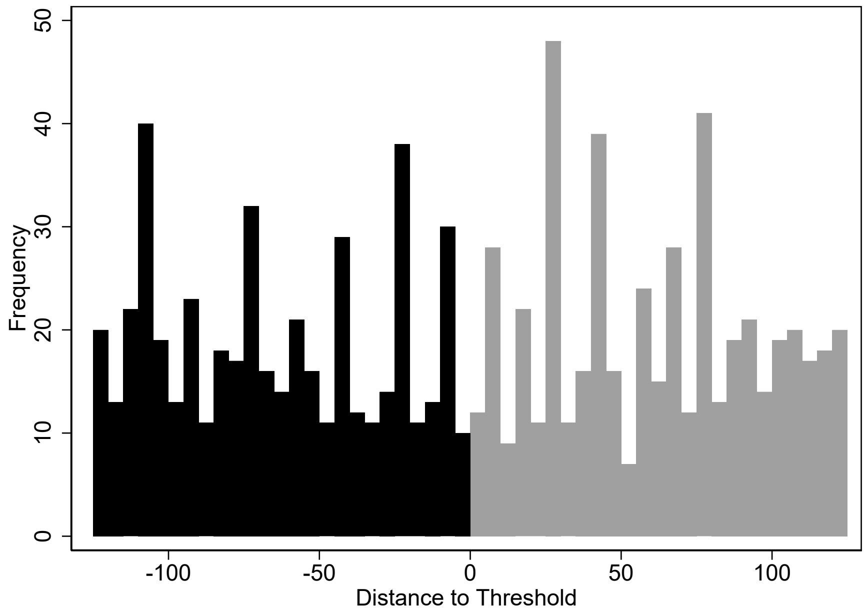
Figure C.3: Subjective Beliefs by Deposits-to-Inflows Quintile



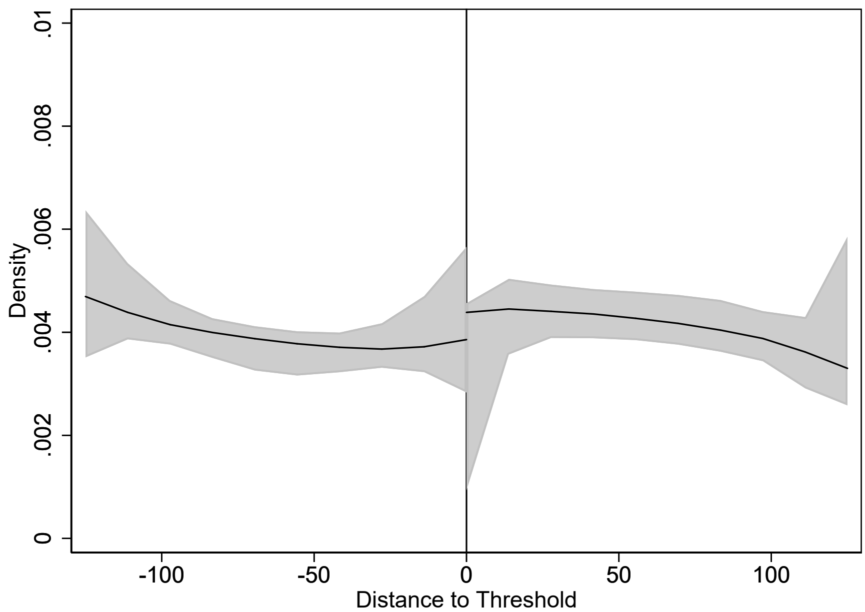
Notes: This figure plots a set of preferences and beliefs dimensions we elicited from users through an ad-hoc survey intervention. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the ratio of deposited amount over income. We limit the sample to users that activate the overdraft facility in our main sample. Vertical bands represent 95% confidence intervals for the point estimates of each quintile.

Figure C.4: Distribution of Forcing Variable around Rounding Thresholds

Panel A: Histogram of Forcing Variable

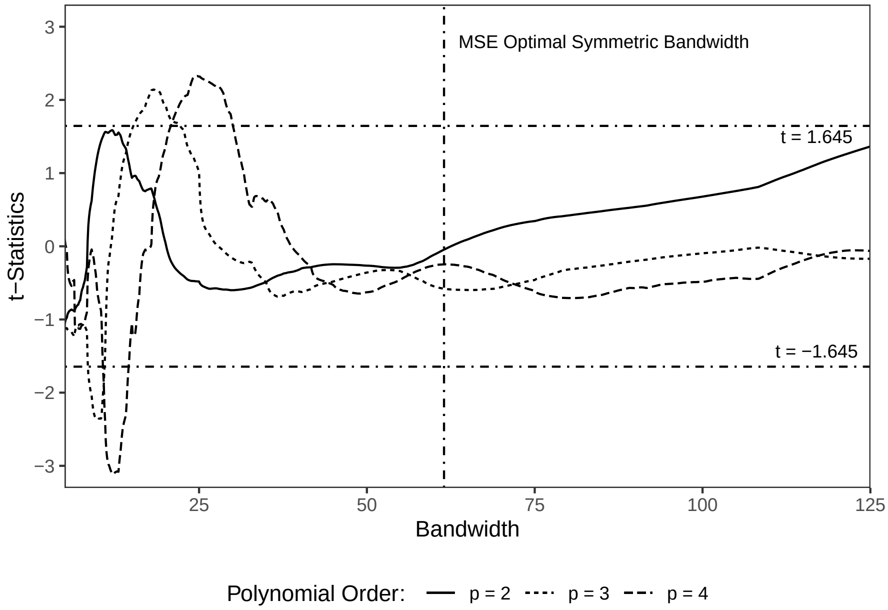


Panel B: Local Polynomial Density Estimate



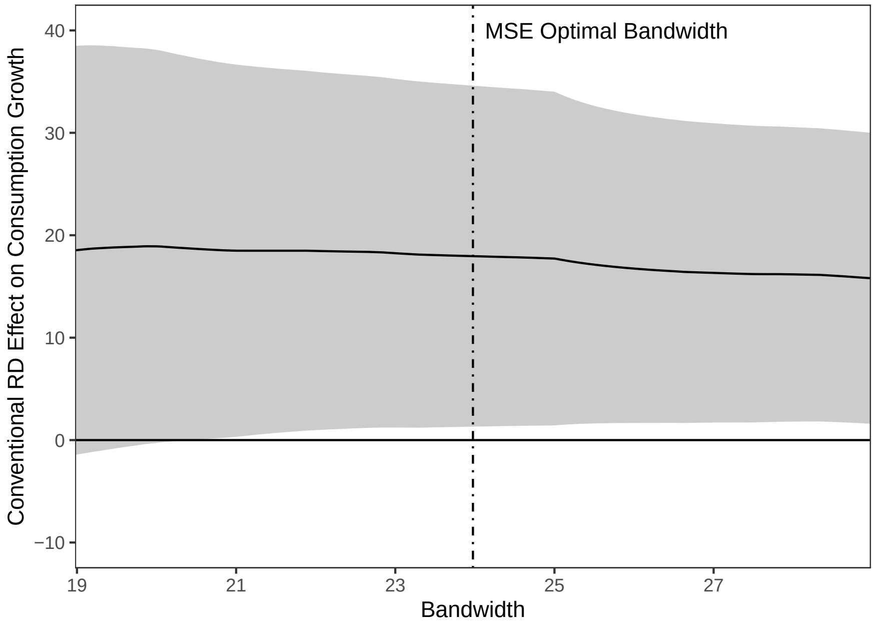
Notes: This figure provides graphical evidence for our treatment manipulation tests in Section 3.6.3. Panel A plots the number of users and Panel B reports the local polynomial density estimate by Cattaneo et al. (2017) for different values of our forcing variable X_i around the rounding threshold.

Figure C.5: Robustness Analyses for Treatment Manipulation Tests



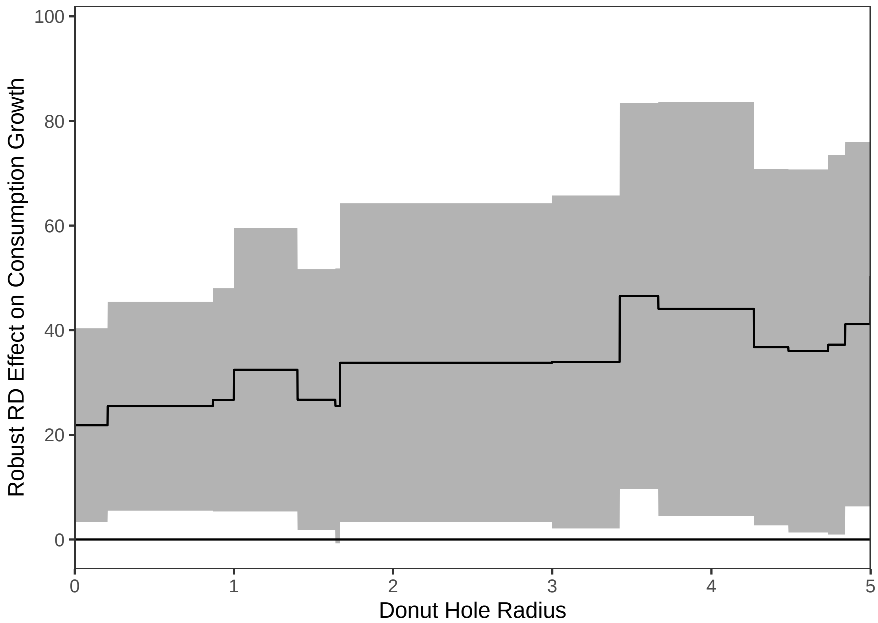
Notes: This figure reports *t*-statistics for the treatment manipulation test by Cattaneo et al. (2017) for different polynomial orders and bandwidth choices. The vertical horizontal lines indicate the critical 10% significance levels at which the test rejects the null hypothesis that our running variable is locally continuous around the rounding threshold.

Figure C.6: Sensitivity of RDD Effects to Bandwidth Choice



Notes: This figure shows convetional regression discontinuity (RD) estimates (solid line) and corresponding 95% confidence intervals (shaded area) for varying bandwidth choices. The figure demonstrates that different bandwidth choices neither substantially affect the magnitude nor the significance of our main RD consumption effect. Varying the bandwidth is only meaningful over small intervals around the mean-squared-error (MSE) optimal choice (Cattaneo et al., 2020). Bandwidths much larger than the MSE-optimal bandwidth bias the RD estimator, while substantially smaller bandwidths inflate its variance.

Figure C.7: Sensitivity of RDD Effects to Observations around Rounding Thresholds



Notes: This figure shows robust regression discontinuity (RD) estimates (solid line) and corresponding 95% confidence intervals (shaded area) for varying donut hole radius choices. This figure demonstrates that our main RD consumption effect is robust to excluding data close to the rounding threshold (e.g., Barreca et al., 2011, 2016). We drop users located within the radius $r > 0$ of the rounding cutoff. Specifically, we exclude observations for which $|X_i| \leq r$ (Cattaneo et al., 2020) and illustrate that observations close to the rounding threshold do not drive our results.

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