Market Design, Human Behavior and Management

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We review past research and forecast future directions on how the rapidly growing areas of market design and behavioral economics have influenced and will continue to impact the science and practice of management in both the private and public sectors. Using examples from various auction markets, reputation and feedback system design in online markets, matching market design in education, and the design of labor markets, we demonstrate that combining market design theory, behavioral insights, and experimental methods can lead to fruitful implementation of superior mechanisms in practice.

1 Introduction

Since the 1990s, economic research has played an increasingly important role in the practical organization and design of markets. The phrase \textit{market design} includes “the design not only of marketplaces but also of other economic environments, institutions and allocation rules” (Roth 2015). Prominent examples of market design include the auctions for spectrum, electricity, and other commodities; tradable permit systems for pollution abatement and other environmental regulations; online auctions; online reputation and feedback systems; financial markets; labor market clearinghouses; formal procedures for student assignment to public schools or colleges; centralized systems for the allocation of organs; and other related matching and trading processes. In many of these cases, theoretical, experimental and empirical research have complemented each other and influenced the design of market institutions.

In the process of bringing a theoretical idea or result to practice, the research strategy is often to observe the performance of the new market design in the context of the simple situations that can be created in a laboratory and assess its performance relative to what it was created to do and relative to the theory upon which its creation rests. For this reason, laboratory experiments are often compared to a wind tunnel. For the rest of this section, we will briefly review several important papers published in \textit{Management Science} related to market design and human behavior.

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At the theoretical level, the most important tool for market design is game theory. In the first 20 years after von Neuman and Morgenstern published their seminal book, Theory of Games and Economic Behavior, game theory largely remained an academic pastime, primarily because of the technical difficulties of modeling games of incomplete information that underlies almost all economic environments of interests (Morris 2019). Between 1967-68, John Harsanyi published three path-breaking papers in *Management Science*, where he successfully argued that we can incorporate any incomplete information without loss of generality as the interim stage of some suitably constructed model of asymmetric information, and extended Nash’s concept of an equilibrium point to games of incomplete information (Harsanyi 1967, 1968a, 1968b). One of the many important results from these papers was the concept of a “type” that summarizes all of the relevant characteristics of a particular player. These three papers provided economists with the much needed tools for studying asymmetric information problems in strategic interactions (Gul 1997).

The first applied area of economics that embraced game theory was industrial organization, which generated many interesting insights on bargaining, contract design, pricing and other practical problems which influenced the theory and practice of management. Game theory has since contributed considerably to virtually all applied theoretical research in economics and political science. Harsanyi’s three *Management Science* papers are broadly considered the precursor to the game theory takeover of economic theory (Morris 2019). Primarily for his contributions in formalizing games of incomplete information, John Harsanyi, together with John Nash and Reinhardt Selten, received The Bank of Sweden Prize in Economic Science in Memory of Alfred Nobel in 1994 (Nobel Foundation, a).

In addition to theoretical foundations for market design, *Management Science* has also published a sequence of influential papers on human behavior. Here we highlight two such papers by researchers pivotal in the creation of the now vibrant field of behavioral economics. The first paper is due to Kahneman and Lovallo (1993), who study choice under uncertainty by focusing on “isolation errors,” whereby people tend to treat risky prospects separately rather than together. In their first “prospect theory” paper, Kahneman and Tversky (1979) raised two central aspects of choice under uncertainty: the role of loss aversion and the probability weighting function. Isolation errors as the third component in risky choice is “something whose centrality to understanding risk attitudes researchers have only begun to fully appreciate” (Rabin 2003). In this paper, Kahneman and Lovallo not only presented experimental results demonstrating the prevalence of isolation errors, but also applied it extensively in the context of managerial decision-making to explain, e.g., the pervasiveness of small-scale insurance policies, such as extended warranties on consumer products, and the equity premium puzzle (Benartzi and Thaler 1995). “For having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty,” Daniel Kahneman shared the 2002 Nobel Prize in Economics (Nobel Foundation, b).

A second paper highlighted here is by Thaler and Johnson (1990), who investigate how risk-taking is affected by prior gains and losses. They present experimental data supporting the “house money effect” whereby decision makers become more risk seeking in the presence of a prior gain, and
“break-even effects” whereby, in the presence of prior losses, outcomes which offer a chance to break even are especially attractive. Summarizing these empirical regularities, they propose an editing rule to describe how decision makers frame such problems. For having built "a bridge between the economic and psychological analyses of individual decision-making" and for his instrumental role “in creating the new and rapidly expanding field of behavioral economics,” Richard Thaler received the Nobel Prize in Economics in 2017 (Nobel Foundation, c).

Finally, Management Science has published a sequence of papers on market design which combines theoretical insights with laboratory experiments to shed light on new market designs. Here we highlight Katok and Roth (2004) who investigate in the laboratory the performance of two “Dutch” auctions for selling multiple homogenous objects, the ascending auctions used in eBay and the descending auctions best known for its use in the flower auctions in the Netherlands. The authors design three environments that include synergies and potentially subject bidders to the exposure problem and the free-riding problem. They find that the descending auctions perform well across environments, while the eBay ascending auction better avoids the free-riding problem. These findings have significant implications for market design for procurement and privatization. Alvin Roth, together with Lloyd Shapley, received the 2012 Nobel Prize in Economics “for the theory of stable allocations and the practice of market design” (Nobel Foundation, d).

As demonstrated in the above examples, Management Science has published foundational work in game theory, human behavior and market design. For the rest of the paper, we will survey several market design challenges and solutions, including sniping in auction markets (Section 2), reputation and feedback system design in online markets (Section 3), matching market design in education (Section 4), and the design of labor markets (Section 5). Finally, Section 6 concludes.

2 Sniping in auction markets

Swift advances in computer and communication technology are creating wonderful opportunities and important challenges for market design. One area of research is concerned with the strategic timing of interaction. In matching markets, Roth and his coauthors analyze and develop mechanisms that address problems arising from incentives to act earlier than others (Roth 1990, 1991, Mongell and Roth 1991, Roth and Xing 1994, Roth and Peranson 1999, Kagel and Roth 2000, Chen and Sönmez 2006, Roth 2008 provides a survey). Competition for people and positions in various job markets led to earlier and earlier dates of appointment, to the point that students were being hired before useful information about their performance was available, and before the students themselves could develop informed career preferences. Roth designed and helped implement successful centralized matching algorithms to stabilize such markets (Roth 2002, and Roth and Wilson 2019 provide an account of the history of market design and of recent developments).

Yet, timing is also an important aspect of strategic behavior in auction markets. As we show in this section, a strategy called “sniping” (bidding as early or as late as possible to gain an advantage) is prevalent in many auction market environments, hampering the efficiency of trade. Market design solutions that can help mitigate sniping are often available. First, we show that sniping is widespread
on C2C online markets like eBay yet can be largely mitigated by changing the rule by which the auctions end. We then sketch how sniping arises in spectrum auctions and can be addressed by activity rules designed to promote better price discovery. Finally, we describe the race for speed in financial markets, why it arises, and how it can make traders worse off and create inefficiencies and market instabilities. Here, too, innovative market design solutions are available.

2.1 Online auctions

Many auctions, including online auctions for consumer goods, are often run in continuous time. The simplest rule for ending such auctions is a fixed end time (a “hard close”), as employed by eBay. A striking property of bidding on eBay is that a substantial fraction of bidders submits their bids in the closing seconds of an auction, which is called “sniping”, just before the hard close. Bidding is different on other platforms such as those formerly run by Amazon, which operated under otherwise similar rules. Amazon auctions were automatically extended if necessary past the scheduled end time until 10 minutes passed without a bid (a “soft close”).

Based on a study by Roth and Ockenfels (2002), Figure 1 shows the empirical cumulative probability distributions of the timing of the last bid in each auction for a sample of 480 eBay and Amazon auctions of antiques and computers with a total of 2,279 bidders. The timing of bids in Amazon is defined with respect to the initially scheduled deadline, which differs from the actual closing time if a bid comes in later than ten minutes before the initial end time.

Figure 1. Cumulative distributions over time of eBay auctions’ last bids (reproduced from Roth and Ockenfels 2002)

Figure 1 shows that there is significantly more late bidding on eBay than on Amazon. For instance, 40 percent of eBay-Computers auctions and 59 percent of eBay-Antiques auctions in the sample have last bids in the last 5 minutes, compared to about 3 percent of both Amazon computer and Amazon antiques auctions that have last bids in the last five minutes before the initially scheduled deadline or later. The pattern repeats in the last minute and even in the last ten seconds. This suggests that changes in the ending rules of auctions can strongly affect bidding behavior. While the Roth and

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1 This section is an adjusted and updated, and much shortened, version of Ockenfels and Roth’s (2013) account of the literature on sniping in auctions for consumer goods.
Ockenfels (2002) study was one of the earliest on eBay, and the data were collected by hand, more recent studies of eBay referenced below use millions of auctions as data and mostly confirm the results.

Sniping on eBay is not easily explained by simple textbook auction analyses. The reason is that there is no time dimension in sealed-bid auctions, and dynamic auctions are typically modeled as clock auctions, where “price clocks” – instead of the bidding itself – determine the pace of the bidding. Moreover, eBay asks the bidders to submit maximum bids (called “proxy bids”). Because eBay’s bidding agent will bid up to the maximum bid only when some other bidder has bid as high or higher, if the bidder has submitted the highest proxy bid, he wins at the “lowest possible price” of one increment above the next highest bid. Thus, similar to the second-price sealed-bid auction, at the end of the auction a proxy bid wins only if it is the highest proxy bid, and the final price is the minimum increment above the second highest submitted proxy bid, regardless of the timing of the bid. This suggests that there is no reason to bid late. Yet, proxy bidding does not necessarily remove the incentives for sniping on eBay. Sniping can avoid bidding wars with incremental bidders, with like-minded late bidders, and with uninformed bidders who look to others’ bids to determine the value of an item (see the series of papers by Roth and Ockenfels (2002), Ockenfels and Roth (2006, 2013), that offers game theoretic analyses for late and incremental bidding strategies, field evidence for strategic late bidding).

For example, sniping can be the best response to the late bidding strategies of like-minded bidders. In 2000, Hal Varian explained the underlying idea in a New York Times column titled “Online Users as Laboratory Rats” as follows: Suppose you are willing to pay up to $10 for a pez dispenser, and there is only one other potential bidder who you believe also has a willingness to pay of about $10. If both of you submit your value early, you will end up with a second highest submitted proxy bid of about $10 implying a price of about $10. Thus, regardless of whether you win or not, your earnings would be close to zero. Now consider a strategy that calls for a bidder to bid $10 at the very last minute and not to bid earlier, unless the other bidder bids earlier. If the other bidder follows this strategy and mutually delay their bids until the last minute, both bidders have positive expected profits, because there is a positive probability that one of the last-minute bids will not be successfully transmitted (Roth and Ockenfels 2002); in which case the winner only has to pay the (small) minimum bid. However, if a bidder deviates from this strategy and bids early, his expected earnings are (approximately) zero because of the early price war triggered by the early bid. Thus, with sniping, expected bidder profits will be higher and seller revenue lower than when everyone bids true values early. That is, sniping can be an equilibrium strategy even with private values and even if there is a risk that the snipe does not make it to eBay in time, before the auction closes.

When values are interdependent, there are additional strategic reasons to bid late in auctions, because the bids of others can then carry valuable information about the item’s value that can provoke a bidder to increase his willingness to pay. This creates incentives to bid late, because by bidding late, less informed bidders can incorporate into their bids the information they have gathered.
from the earlier bids of others, and experts can avoid giving information to others through their own early bids (Bajari and Hortaçsu 2004, Ockenfels and Roth 2006, Hossain 2008).

Finally, last minute bidding can also be a best reply to incremental bidding. To see why, suppose you believe that your competitor starts with a bid well below his maximum willingness to pay and is then prepared to raise his proxy bid whenever he is outbid, as long as the price is below his willingness to pay. Last-minute bids can be a best response to this kind of incremental bidding because bidding near the deadline of the auction would not give the incremental bidder sufficient time to respond to being outbid. By bidding at the last moment, you might win the auction at the incremental bidder’s initial, low bid, even when the incremental bidder’s willingness to pay exceeds your willingness to pay. Non-strategic reasons for incremental bidding include that bidders may not be aware of eBay’s proxy system and thus behave as if they bid in an ascending (English) auction, ‘endowment effect’ (Roth and Ockenfels 2002, Wolf et al. 2005 and Cotton 2009), ‘auction fever’ (Heyman et al. 2004), escalation of commitment and competitive arousal (Ku et al. 2005), uncertainty over one’s own private valuation (Rasmusen 2006), or an unwillingness to reveal one’s valuation (Rothkopf et al. 1990). Strategic reasons include shill bidding by confederates of the seller to push up the price beyond the second-highest maximum bid (Engelberg and Williams 2009), and a strategic response to the multiplicity of listings of similar objects (Anwar et al. 2006, Peters and Severinov 2006).

Amazon auctions are automatically extended if necessary past the scheduled end time until ten minutes have passed without a bid. Although the risks of last-minute bidding remain, the strategic advantages of last-minute bidding are eliminated or severely attenuated in Amazon-style auctions, because no matter how late a bid was placed, other bidders will have time to respond. Thus, on Amazon, an attentive incremental bidder, for example, can respond whenever a bid is placed. As a result, the advantage that sniping confers in an auction with a fixed deadline is eliminated or greatly attenuated in an Amazon-style auction with an automatic extension (Ockenfels and Roth 2006, Malaga et al. 2010). Indeed, Figure 1 suggests that late bidding arises in large part from the rational response of the bidders to the strategic environment. Moreover, more experienced bidders on eBay bid later than less experienced bidders, while experience in Amazon has the opposite effect (Ariely et al. 2005, Ockenfels and Roth 2006, Wilcox 2000). In addition, since significantly more late bidding is found in antiques auctions than in computer auctions on eBay, but not on Amazon, behavior responds to the strategic incentives created by the possession of information, in a way that interacts with the rules of the auction.

Laboratory experiments conducted by Ariely et al. (2005) replicate the major field findings in a controlled laboratory private-value setting in which the only difference between auctions is the ending rule. Moreover, the laboratory Amazon condition turns out to be more efficient and to yield higher revenues than the other conditions; the field evidence on efficiency and revenues from various auction platforms is, however, somewhat more mixed (Glover and Raviv 2012, Gray and Reiley 2013, Cao et al. 2019, Brown and Morgan 2009, Houser and Wooders 2005, Elfenbein and McManus 2010 and Carpenter et al. 2011). Backus et al. (2015) find another harmful impact of sniping based on eBay
field data: being sniped discourages new bidders from returning to bid again – they are between 4 and 18 percent less likely to return to the platform.

The next subsections describe two other important examples for sniping in markets, examples in which traders are – unlike on eBay – most sophisticated and in which very different solutions to address sniping have been devised.

2.2 Spectrum auctions

Spectrum auctions have been used by governments to assign and price spectrum for about 25 years. Over those years, many design issues have surfaced. Like on eBay (which was founded in 1995, around the same time when spectrum auctions started to become popular), one important challenge is sniping—jumping in at the last instance in an auction.

The workhorse for spectrum auctions since 1994 has been the simultaneous ascending auction, which is a simple generalization of the English auction to multiple items in which all items are auctioned simultaneously. Thus, unlike Sotheby’s or Christie’s auctions in which the items are auctioned in sequence, here all the items are auctioned at the same time: Each item has a price that is associated with it. Over a sequence of rounds, bidders are asked to raise the bid on any items that they find attractive, and the auctioneer identifies the provisional winner for each item at the end of every round. The process continues until nobody is willing to bid any higher – which is related to Amazon’s soft close auction. This process was originally proposed by Preston McAfee, Paul Milgrom, and Robert Wilson for the FCC spectrum auctions.

Although these auctions end with a soft close, bidders may want to hold back, not pushing up prices on those objects they value most and concealing their private information until the end of an auction. One motivation for this strategy stems from an aggregate budget constraint. It may be easier to push a competitor aside late in the auction when the competitor has already committed its budget in other markets. A second motivation is a desire to better understand prices before committing to a specific portfolio of spectrum assets.

Sniping, however, slows the auction down and prevents price discovery. Yet good price discovery is essential in realizing the benefits of complex, dynamic auctions. One reason is that there is much uncertainty about what the objects being sold are worth. The bidders typically can only develop a crude valuation model. They need the benefit of some collective market insights, which can be revealed in a dynamic auction process to improve their bidding. If the price discovery process works

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2 This section is mostly based on, and partly taken from, Cramton (2013).
3 Klemperer (1998, 2002) proposes an ending rule for spectrum auctions that is somewhat closer to eBay’s hard close, namely a hybrid of the ascending, soft-close auction format and the sealed-bid format, which he calls “Anglo-Dutch”. The idea is that the early bidding is like in the simultaneous ascending auction, but bidders can make final sealed-bids at the end of the auction. Klemperer argues that this kind of hard-close can discourage collusion in the dynamic phase of the auction, because the last-minute round allows bidders to renege on any deals without fear of retaliation, and because the final bids induce some uncertainty about the winner, this can also attract entrants. Such concerns are not relevant for the choice of eBay’s hard-close ending rule in their single-object auctions, though.
4 Studies on eBay reveal that bidders do not bid truthfully early in the auction, but that much of the price discovery is done only in the closing seconds of the auction (e.g., Ariely et al. 2005).
The standard solution in spectrum auction design is an “activity rule”. The activity rule requires a bidder to be active (that is to be the current high bidder or to submit new bids) on a predetermined quantity of spectrum licenses. If a bidder falls short of the required activity level, the quantity of licenses it is eligible to buy shrinks. Thus, bidders are prevented from holding back. The activity rule avoids late bidding and controls the pace of auctions by creating pressure on bidders to bid actively from the start. Milgrom and Wilson designed an activity rule that was applied to the U.S. spectrum auctions (McAfee and McMillan 1996, Milgrom 2004). Nearly all high-stake auctions, such as the FCC spectrum auctions, have an activity rule.

The exact design of the activity rule depends on the auction environment. More complex auctions require more complex activity rules. Too strong activity rules might force bidders to bid for less than their true demands, and too weak activity rules will inevitably lead to late bidding. For a single-object spectrum auction, a reasonable activity rule would require that no bidder can re-enter after exiting the auction. In an eBay-like auction, for instance, the activity rule would imply that all bidders, right at the start, submit their maximum willingness to pay as a proxy bid. No bidder could enter the auction once it started or re-enter once the bidder exited. (This, of course, would be incompatible with the flexibility needed on C2C auction platforms, but it is compatible with spectrum auctions where there are discrete rounds that follow a daily schedule.) For a multi-unit auction of a single product, the activity rule would require that one cannot increase demand as price increases. For many related products, an aggregate quantity rule is needed, which requires that bidders are active on a particular fraction of current “eligibility” or the eligibility is reduced. In more complex auctions, such as combinatorial clock auctions, state-of-the-art revealed preference rules can make sure that, as prices increase, bidders can only shift toward packages that become relatively cheaper (Ausubel et al. 2006, Ausubel and Baranov 2019).

What happens without an activity rule can be observed in spectrum auctions such as the Italy 4G auction, which did not have an activity rule. As a result, bidders held back demand, slowing the auction and limiting price discovery. Eventually, the auction lasted 470 rounds. That said, Germany’s recent 5G auction, in 2019, lasted 497 rounds and thus set a new world record with respect to number of rounds in a simultaneous ascending auction. Here, the flaw was not the activity rule, but the fact

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5 Here, each lot corresponds to a specific quantity of spectrum, measured in either MHzPop or in “eligibility points”. The bidder starts with an initial eligibility based on the bidder’s initial deposit. To maintain this level of eligibility in future rounds, the bidder needs to bid on a sufficiently large quantity of spectrum in the current round, where “sufficiently large” is stated as some percentage, typically between 80% and 100% of the bidder’s current eligibility. If the bidder bids on a smaller quantity, the bidder’s eligibility is reduced in future rounds.
that it would take many rounds to get a one increment increase in price, because Germany used the traditional simultaneous ascending auction with bidding on individual lots, rather than a modern clock auction, which has prices increase by a bid increment in each round for any product with excess demand (see Cramton and Ockenfels 2017 for an analysis of the German spectrum auction design). Measures to address sniping cannot be analyzed in isolation but must be closely connected to other details of the rules, such as pricing rules and increment rules to be fully effective.

2.3 Financial markets

Markets for financial securities are another important example where market design has a profound impact on the incentives for sniping and speed in markets. Unlike in spectrum auctions, the problem is not that bids tend to be held back, but rather a never-ending arms race for ever faster trading. Because trading is continuous and equally attractive orders are processed in the order they arrive, speed is crucial in this format. This limits the performance of these markets (e.g., Budish et al. 2019a). As before, the problem can be viewed with the lens of market design. This reveals a solution as presented in Budish et al. (2015), which we describe below.

The root of the problem is a fundamental flaw in today’s markets: continuous-time trading. Continuous-time trading means that it is possible to buy or sell securities at any instant, where instant is measured in billionths of seconds – the speed of today’s computers. Thus, the solution is for trading to occur in discrete time. Instead of trading at any instant, trading occurs, say, once per second. Orders arriving in the same second are batched together without any priority for orders that arrive a bit earlier, and all trades occur at the same price where supply and demand cross. The key is that the trading interval should be short as perceived by humans, but long for a computer.

But what exactly is wrong with continuous trading? Is trading as fast as possible not just good for price discovery and healthy competition, as probably suggested by our discussion of the need for activity rules in spectrum auctions? The answer boils down to a combination of two market failures. The first market failure is that in times of algorithmic trading, continuous markets do not and cannot, work as they should in continuous time. Equivalent securities with prices that move in lockstep at human time intervals have moments of significant divergence at high frequencies. This creates what economists call technical arbitrage opportunities: the kinds of opportunities that are not supposed to exist if the market is working properly. For example, the price of the S&P 500 futures contract in Chicago (ES) and the S&P 500 EFT in New York (SPY) should move in perfect lockstep, and to the human eye they do (Figure 2 left panel). But, when we zoom in to high frequency, there are hundreds of opportunities a day to make nearly riskless money – buy low in New York and sell high in Chicago, or vice versa (Figure 2 right panel). This adds up to about $75 million a year for high frequency traders – and this is just one pair of securities. There are hundreds of other pairs just like it, and, in our fragmented US equities markets, trades that are even simpler: if a stock jumps up on NASDAQ, buy it low on NYSE.
The second market failure is that these technical arbitrage opportunities – which are a prize to whichever trader snaps them up the fastest – create a never-ending arms race for speed. This fight for the prize is why there are investments like the $300 million high-speed cable between New York and Chicago – and why that cable is already obsolete. This is why there are armies of physics and computer science PhDs devoted to shaving millionths or billionths of seconds off of trading times. This is also why there are exchanges renting colocation services and high-speed data feeds – that is their way of getting a piece of the prize. Here is a simple way to think about it: continuous-time trading creates a $10 billion prize, and then high-frequency traders, exchanges, and broker-dealers all scramble to get their piece.

Ultimately the prize comes out of the pockets of investors. The reason is that the technical arbitrage opportunities harm liquidity – it is harder to provide quotes to investors if one is constantly worried that prices will change and one’s stale quotes will get picked off before one can revise them. So, markets are less liquid than they should be. And for institutional investors this means trading large blocks of stock is costlier.

Discrete time directly addresses both market failures. With discrete time, one cannot make money from exploiting pricing discrepancies that many traders see at the same time – just by acting a billionth of a second faster. This stops the arms race for speed. Unhealthy competition for speed is transformed into productive price competition. Trades occur at the right price – the consensus of the market – rather than at stale quotes. High-frequency traders still will be able to make money, but only if they take actual risk, provide liquidity, or are smarter than the rest of the market – know something that the rest of the market does not. One no longer can make money just from being the fastest to respond to some commonly observed event.

Discrete time also makes computational sense. Continuous trading implicitly assumes that computers and communications are infinitely fast. Computers and communications are fast but not infinitely so. Discrete time respects these limits. Tiny speed discrepancies between the direct feeds
and public feeds of exchange data are critical with continuous time. This issue goes away with discrete time.

Continuous time breeds constant change and heightened complexity, making markets vulnerable to instability. Discrete time simplifies markets and allows both traders and exchanges to focus on improvements that make trading smarter and safer.

Which market design works in the financial sector to address sniping is the topic of many current discussions. Discrete time has seen limited implementation and alternative design solutions have been proposed. For example, in 2016, the U.S. Securities and Exchange Commission approved the Investors Exchange (IEX) to operate as a public securities exchange. A primary goal of the IEX market, which was founded in 2012 to provide an alternative trading system with delayed messaging (Aldrich and Friedman 2018) is to reduce potential advantages of HFT firms. Another alternative is randomization of order priority as employed by Electronic Broking Services (EBS), the largest currency exchange in the world. Asymmetric speed bumps – delaying sniping orders but not order cancelations – are now common. Other innovative methods such as flow trading are also being studied (Kyle and Lee 2017, Budish et al. 2019b).

Unlike in spectrum and online auctions, which have experimented with various auction architectures both in the laboratory and the field, there is not much conclusive and clean causal empirical evidence yet that can guide market design for financial securities. Zhang and Riordan (2011), Brogaard et al. (2014), Benos and Sagade (2016), Benos et al. (2017), and Menkveld and Zoican (2014), among others, provide evidence for the costs of aggressive sniping. However, this literature comes from minor variants of the standard financial market design, and thus offers no direct evidence about the costs and benefits of other platforms, engineered to eliminate the dilemma. Moreover, even though there are three decades of studying financial markets in the laboratory (for surveys on experimental research in financial markets see, e.g., Friedman 2010, Noussair and Tucker 2013, and the standard reference on financial market formats by Friedman and Rust 1993), aside from particular episodes such as the “Flash Crash” (Aldrich et al. 2016), little is known about the impact of sniping in times of financial stress as opposed to normal times. However, Aldrich and López Vargas (2019) recently conducted a laboratory market design study on high-frequency trading that suggests that, relative to the continuous double auction, the frequent batch auction exhibits less predatory trading behavior, lower investments in low-latency communication technology, lower transaction costs, and lower volatility in market spreads and liquidity. More studies on how financial market design affects sniping, market stability and market resiliency are necessary.

Summing up, we note that there are many important topics in auction design beyond sniping (surveys are provided by, e.g., Bichler and Goeree 2017, Cramton et al. 2006, Milgrom 2004, 2017, forthcoming, Klemperer 2004, Greiner et al. 2012). Yet with the advent of online, spectrum and agent-based auctions and algorithmic bidding, controlling the pace of price discovery became one of the most pressing topics in market design research, one that was not anticipated by auction theory, but rather inspired by practical challenges, low market performance and failed design attempts. Analyses of spectrum, online and financial markets demonstrate that sniping can often be explained
by equilibrium predictions. Much of the late bidding in C2C online auctions such as eBay, on the other hand, is often best explained by a strategic response to naïve, incremental bidding, yet it can also arise at equilibrium in both private- and common-value auctions. Indeed, the effect of the fixed deadline is likely as large as it is because it rewards late bidding both when other bidders are sophisticated and when they are not. Market design must sometimes consider not only the equilibrium behavior that we might expect experienced and sophisticated players eventually to exhibit, but also how the design affects behavior of inexperienced participants, as well as the interaction between sophisticated and unsophisticated human players and algorithmic bidding-agents.

Another auction context where much has been learned from laboratory human-subject research is the practical design of procurement auctions, with much research published in Management Science (e.g. Chaturvedi et al. 2014, Fugger et al. 2015, Davis et al. 2011, 2014, Engelbrecht-Wiggans and Katok 2008, and Katok and Roth 2004).

There are many challenges for future research. For instance, while policy makers worldwide are already taking actions intended to discourage high frequency trading, no scientific evidence exists on the relative performance of financial market institutions that are designed to mitigate high frequency trading. Also, many other markets, as they move to real-time interaction, already see or will likely see similar problems, and thus require new clever market design solutions. As an example, think about electricity market design, where we are just starting to observe similar issues. Another important example is auction design for continuous sponsored search in the Internet, where other undesired bidding timing phenomenon have been observed, such as bidding cycles with automated bidding agents, as well as various attempts to address those (e.g., Edelman and Ostrovsky 2007, Edelman et al. 2007, Varian 2007, 2009, Athey and Ellison 2011, Levin 2013 provides a survey). Taming sniping is and will be a critical aspect of market performance in modern market environments.

3 Reputation and feedback system design in online markets

The astonishing success of online market platforms such as eBay, Amazon, Uber, and Airbnb can be attributed to the ease in which one side of the market can find a match on the other market side, as well as to the fact that they provide reliable information about the trustworthiness of the trading.

6 Ely and Hossain (2009) suggest on the basis of their field experiment that the availability of closely substitutable auctions on eBay may reduce the overall benefit of sniping.

7 In electricity markets, one reason is the increasing share of intermittent renewables, which puts enormous stress on the system and increases the risk of outages, so that both, improved investment incentives for reserve generation capacity (Cramton and Ockenfels 2012, Cramton et al. 2013) and more liquid real-time trading, is needed. Yet, because the trend towards algorithmic trading in continuous electricity markets will also lead to a wasteful race for speed, this is posing serious threats to the efficiency and reliability of these markets (Neuhoff et al. 2016). Moreover, compared to financial markets, things tend to be more complicated in electricity markets because of complementarities in electricity production (Wilson 2002 and Cramton 2017). For instance, the race for speed in electricity trading hampers efficient pricing of transmission, which is often done on a first-come-first-serve basis in intraday trading. Also, a race for speed complicates the formulation and consideration of multi-dimensional bids, which consider the non-convex cost structure of electricity production.
partner. All markets require some minimum amount of trust, yet this is a particular challenge for online markets and sharing platforms, where trades are typically with strangers, geographically dispersed, and executed sequentially. To incentivize trustworthiness, most online platforms employ a reputation-based ‘feedback system’, enabling traders to publicly post information about past transaction partners. These systems have been, and are being, engineered based on conceptual insights from game theory and behavioral sciences, and with the help of laboratory and field studies (surveys include Dellarocas 2003, Bar-Isaac and Tadelis 2008, Greiner and Ockenfels 2009, Ockenfels and Resnick 2012, Bolton and Ockenfels 2012, Tadelis 2016, Gut et al. 2019).

One major challenge of all feedback-based reputation systems is to get people to cooperate with the platform and leave feedback about their transaction partner. Feedback information is largely a public good, helping other traders to manage the risks involved in trusting an unknown transaction partner, so economists would tend to predict low participation rates. Yet, in the field data by Bolton, Greiner and Ockenfels (2013), about 70% of the eBay traders, sellers and buyers alike, leave feedback (a number consistent with other research). It turns out that the key driver of provision of feedback, as well as the source of various distortions in feedback information identified in the literature, is reciprocity. More specifically, much of the feedback patterns we see can be organized by connecting them to two of the most fundamental research findings on the patterns of human cooperation in the last decades: altruistic punishment promotes cooperation, and counter-punishment hampers cooperation (Ostrom et al. 1992, Fehr and Gächter 2000, 2002, Nikiforakis 2008, Mussweiler and Ockenfels 2013, Balafoutas et al. 2014). A natural way to (altruistically) punish a trader on an Internet platform who is not behaving according to what is perceived to be the social or trading norm, is to leave negative feedback. This way, a propensity to altruistically punish norm-violators creates an incentive to be trustworthy. However, punishments can often be counter-punished, which is known to reduce the effectiveness of punishment to promote cooperation. Indeed, by retaliating a negative feedback with a negative one, counter-punishment may spoil the reputation of the altruistic punisher, which in turn may deter altruistic punishment in the first place. As a result, the potential of counter-punishment can hamper the effectiveness of reputation mechanisms and thus the performance of markets.

To illustrate the close analogy between (counter-)punishment in the behavioral science literature and giving feedback in the Internet, look at the figure below, which is taken from Bolton et al. (2013). It shows the timing of feedback given on eBay by the buyer and the seller in hundreds of thousands of transactions. Most transactions either end with mutually positive (green dots), or with mutually negative feedback (red dots). Transactions with mutually positive feedback are all over the place (although a closer look at the data in Bolton et al. reveals that there is lots of reciprocity: many traders give ‘kind’ feedback in reciprocal response to ‘kind’ feedback). Transactions with mutual negative feedback, on the other hand, are highly clustered just below the diagonal. This means that many sellers, who are punished with a negative feedback from their buyers, respond immediately by counter-punishing with a negative feedback. Clearly, feedback giving is not independent. The tightness and sequence in timing rather strongly suggest that sellers reciprocate positive feedback
and ‘retaliate’ negative feedback. Seller retaliation also explains why more than 70% of cases in which the buyer gives problematic feedback and the seller gives positive feedback (blue dots in Figure 2), involve the buyer giving second – the buyer going first would involve a high risk of retaliation. Observations in which only the seller gives problematic feedback (yellow dots) are rare and have their mass below the 45-degree line.

Figure 3. Reciprocity in feedback giving (reproduced from Bolton et al. 2013)

There are benefits and costs of reciprocity in feedback giving. A benefit of reciprocal positive feedback, for both the individual traders involved and the larger system, is that it helps getting mutually beneficial trades recorded. But in the form of seller retaliation, reciprocal feedback imposes costs both on the buyers retaliated against and potentially on the larger system (because traders might not be willing to leave negative feedback out of fear that it will be retaliated). This would bias feedback information to be overly positive and therefore less informative in identifying problem sellers. Indeed, on eBay, almost all feedback is positive. Using internal eBay data, Nosko and Tadelis (2015) find that traders’ positive feedback percentage is 99.3% with a median of 100%. The concern is also supported by Dellarocas and Wood (2008) who examine the information hidden in the cases where feedback is not given. They estimate, under some auxiliary assumptions, that buyers are at least mildly dissatisfied in about 21% of all eBay transactions, far higher than the levels suggested by the reported feedback. They argue that many buyers do not submit feedback at all because of the potential risk of retaliation. Controlled laboratory evidence in Bolton et al. (2013) supports the notion that counter-punishment in feedback giving reduces the effectiveness of reputation building and market performance.
Yet, online reputation systems can be designed to address flaws in the system. Bolton et al. (2013) demonstrate that reciprocity can be guided by changing the way feedback information flows through the market system, leading to more accurate reputation information, more trust and more efficient trade. Specifically, their data show that, compared to the simple two-sided feedback system traditionally implemented by eBay, where buyers leave feedback on sellers and vice versa, both blind and one-sided feedback significantly reduce the scope for retaliation, which in turn increase the informativeness of the feedback presented to buyers. The result is in line with game theory, behavioral science, laboratory and field research on social behavior and reputation building (such as the line of research by Bolton et al. 2004, 2005, Bolton and Ockenfels 2009, 2014), and with field data collected across various market platforms. Indeed, the idea of making altruistic punishment easy but counter-punishment difficult explains important features of today’s running reputational feedback systems. For instance, eBay supplemented their old two-sided feedback system with a one-sided system (called “detailed seller rating”). Based on research by Bolton et al. (2013), the one-sidedness was designed so that feedback cannot be retaliated by sellers. Airbnb, also inspired by the line of behavioral research described above and their own experimental findings, created a blind feedback system, where transaction partners cannot see the others’ feedback until they left their own. This, too, makes it impossible to retaliate negative feedback (although a recent study finds the effect to be small on Airbnb; Fradkin et al. 2019). Uber, on the other hand, makes it hard for passengers to see their reputation, and to identify a specific feedback giver, which is another way of making it difficult to retaliate negative feedback. Finally, eBay changed its systems again in 2008 so that sellers can only leave positive feedback, which was meant to eliminate the scope for counter-punishment.

There are still important gaps in our knowledge, and much more experimenting is needed to further improve trustworthiness and cooperation in online markets. For instance, because eBay’s 2008 feedback system removes counter-punishment by sellers, buyers welcomed the new design (Klein et al. 2016). But there are a number of indications that many sellers are unhappy with the new system. The reason is that by removing the option to counter-punish, the new system also removes the option to punish buyers, and thus mitigates buyers’ incentives to cooperate. To the extent that there is scope for moral hazard on the buyer side, this creates an imbalance of punishment (and thus bargaining) power between buyers and sellers. Thus, the overall effect of removing the sellers’ punishment option on cooperation and market performance is probably more ambiguous than the Klein et al. study (2016) suggests. From a broader perspective, the question how the rules affecting the scope for punishment and counter-punishment in interactions with two-sided moral hazard should be shaped largely remains an open one.

More recent attempts to incentivize, filter, and de-bias human judgment involve financial compensation for feedback information (see Li 2010, Li and Xiao 2014, and Li et al. 2016 for case studies on Alibaba, Cabral and Li 2015 for field experiments on eBay, and Burtch et al. 2018), plans to rely more on big behavioral data and artificial intelligence to better predict future behavior (Milgrom and Tadelis 2018, Masterov et al. 2015, Luca and Zervas 2016), and on blockchain technology to better verify and audit transaction attributes (Catalini and Gans 2019).
Another pressing question in reputation design is whether and how traders can modify already submitted feedback information. One example is whether traders should be allowed to remove an initially given negative feedback if the dispute could later be resolved. Many platforms, including eBay.com, etsy.com, discogs.com, ricardo.ch, tradingpost.com.au, trademe.co.nz, mercadolibre.com, and listia.com, have or had a system that withdraws negative feedback from both traders’ reputation profiles – if and only if both traders agree. Among other things, this option is thought to incentivize conflict resolution. However, Bolton et al. (2018) have shown both, theoretically and empirically, that this system is flawed in that it creates incentives to distrust, escalating conflict instead of resolving it. The reason is that the system allows traders to use counter-punishment to protect untrustworthy behavior: If I counter-punish a negative feedback that I received, my opponent will more likely agree to remove that negative feedback (because otherwise his reputation will be spoiled, too). However, there is a lack of research that can guide the design of rules to integrate effective dispute resolution and informative reputation building systems (but see Ockenfels and Resnick 2012 and Bolton et al. 2019).

There is also a lack of knowledge regarding feedback giving, content and usage in credence good markets, such as markets for medical, financial or technical repair services. One major difference to the kind of online markets we have discussed so far is that consumers are often persistently unable to identify the quality of service that fits their needs best. This poses new challenges to designing effective and behaviorally robust mechanisms that promote trust and trustworthiness in these markets (Balafoutas et al. 2013, 2017, Dullecet al. 2011, Kerschbamer et al. 2016, 2019).

We finally emphasize that research on “engineering trust” in online markets has been inspired by practical design problems. Indeed, standard reputation theory did hardly anticipate the kinds of problems that online markets face when implementing reputation systems. Theory often assumes that reputation information is perfectly accurate and complete. Under these conditions, we can expect to see perfect reputation building, and perfect trust, among market actors (Wilson 1985, Bolton et al. 2011), and there is no scope for an engineering literature that guides attempts to effectively promote the provision of informative feedback in practice. On the other hand, behavioral research and experimental studies turned out to be useful in organizing the relevant patterns observed in the field. A desirable next step is to learn from such observations and develop new analytical models of the relevant institutional details and behavioral complexities in the field. For instance, while there has been much progress in modeling social behavior in the last two decades, including models of fairness and reciprocity (see Cooper and Kagel 2016 for an overview), as well as theoretical mechanism design implications of social preferences (Bierbrauer et al. 2017), no social preferences model captures the relevant punishment and counter-punishment patterns within an equilibrium framework (Engel 2014 and Dhami 2016 survey the literature). There is also comparatively little research on the psychological and social determinants of the production of reputation information, connecting the fundamental behavioral science literature on punishment and the practical market design literature on feedback giving. Interesting variables include the role of comparison processes for feedback giving and punishment (Chen et al. 2010, 2019, Mussweiler

4 Matching markets in education

While auction markets use prices to coordinate demand and supply, most of the centralized matching markets take agents’ reported preferences as inputs and feed them into various matching algorithms to determine who gets what. Matching theory has been applied to many important design and management problems in both the private and public sectors, such as school choice, college admissions, course allocation and entry-level labor markets. The practical design application of matching theory starts with the redesign of the National Residence Matching Program (Roth and Peranson 1997), and has since evolved into a research program that addresses practical market design problems using game theory, laboratory and field experiments, as well as computation methods (Roth 2002).

In what follows, we provide three examples of how a combination of economic theory and laboratory experiments inform the implementation of better education policies and management practices.

4.1 Re-design school choice mechanisms

School choice has been a widely-debated education policy across the world, affecting the education experiences and labor market outcomes for millions of students each year. The past two decades have witnessed major innovations in this domain. For example, shortly after Abdulkadiroğlu and Sönmez (2003) was published, New York City high schools replaced their allocation mechanism with a capped version of the student- proposing deferred acceptance (DA) mechanism (Gale and Shapley 1962), a less manipulable and more stable mechanism advocated by matching theorists involved in the design process (Abdulkadiroğlu et al. 2005a). In 2005, the Boston Public School Committee voted to replace its Boston immediate acceptance school choice mechanism (IA) with DA (Abdulkadiroğlu et al. 2005b) after IA was shown to be vulnerable to strategic manipulation both theoretically (Abdulkadiroğlu and Sönmez 2003, Ergin and Sönmez 2006) and experimentally (Chen and Sönmez 2006). In this case, experimental data helped make the case for DA in Boston’s decision to switch from IA in 2005 (Abdulkadiroğlu et al. 2005b).

Within school choice research, matching mechanisms that have received significant scholarly attention include the Gale-Shapley Deferred Acceptance mechanism (Gale and Shapley 1962), the Boston Immediate Acceptance mechanism (Abdulkadiroğlu and Sönmez 2003), the Top-Trading-Cycles (TTC) mechanism (Abdulkadiroğlu and Sönmez 2003), and variants of the serial dictatorship mechanism (Pathak and Sönmez 2013). Indeed, the question of which mechanism best meets the goals of a school choice plan has been at the center of intensive research as well as ongoing policy discussions (Abdulkadiroğlu and Sönmez 2003, Ergin and Sönmez 2006, Abdulkadiroğlu et al. 2011).

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8 This section is based on, and partly taken from, the school choice literature review in Chen et al. (2018) and Chen and Kesten (2019).
We first briefly introduce the school choice mechanisms, summarize their theoretical properties, and performance in the laboratory and field when applicable. We then discuss the major school choice reforms around the world concerning the abandonment or adoption of some of these mechanisms. Our first mechanism, IA, is the most common school choice mechanism observed in practice in China, the United Kingdom and the United States. Its outcome can be calculated via the following algorithm:

**Step 1:** For each school, consider only those students who have listed it as their first choice. Those students among them with the highest priority for that school are assigned that school up to its quota. The remaining applicants are rejected.

**Step k, k ≥ 2:** Consider the remaining students who are unassigned and the schools that have not filled their quota. For each such school, consider only those students who have listed it as their k-th choice. In this group, those students with the highest priority for that school are assigned that school up to its remaining quota.

The algorithm terminates when there are no students left to assign or no school seats remain. Importantly, note that the assignments in each step are final. Based on this feature, an important critique of IA is that it gives students strong incentives for gaming through misreported preferences. That is, a student who has high priority for a school under IA may lose her priority advantage for that school if she does not list it as her first choice. Consequently, IA forces students to make hard and potentially costly choices, which leads to a high-stakes game among participants with different levels of strategic sophistication. This has been observed in the laboratory among financially motivated subjects (Chen and Sönmez 2006), as well as in the field, using naturally occurring data from Boston (Pathak and Sönmez 2008). Recognition of these deficiencies of IA has lead both Boston and New York City to abandon IA and replace it with DA.

Outside of the United States, variants of IA have been used as a school choice mechanism in China, the United Kingdom and France. In China, to equalize access to school resources across students of different socioeconomic backgrounds, the Chinese government abandoned the previous merit-based middle school admissions mechanism in 1998, and replaced it with an open enrollment school choice mechanism where parents rank schools and schools select students using IA (Lai et al. 2009). Since then, students applying for middle schools are prioritized on the basis of their residence, whereas those applying for high schools are prioritized based on their municipal-wide exam scores. Using public middle school admissions data from Beijing Eastern City District, He (2014) investigates parents’ behavior and finds that parents are overcautious in that they play “safe” strategies too often. Combining survey data, middle school choice data and High School Entrance Exam test scores from Beijing, Lai et al. (2009) find that children of parents who made mistakes in middle school selection were admitted to lower quality schools and achieved lower test scores on the High School Entrance Exam three years later. Despite these problems, IA continues to be used as the major school choice mechanism in China.
Our second mechanism is the student-proposing deferred acceptance mechanism (Gale and Shapley 1962), which has played a central role in the school choice reforms in Boston and New York City (Abdulkadiroğlu et al. 2005b,a), as well as in Finland, Ghana, Paris (Fack et al. 2019), Romania, Singapore and Turkey. The outcome of this mechanism can be calculated via the following deferred acceptance (DA) algorithm:

**Step 1:** Each student applies to her favorite school. Each school tentatively retains those applicants who have the highest priority at that school. The remaining applicants are rejected.

**Step k, k ≥ 2:** Each student rejected from a school at step k−1 applies to his next choice school. Each school then tentatively retains those applicants who have the highest priority among the new applicants as well as those tentatively retained at an earlier step. The remaining applicants are rejected.

The algorithm terminates when each student is tentatively retained at some school. Note that, in DA, assignments made at each step are temporary, until the last step. This feature contributes to the desirable properties of DA in terms of incentives and stability. One advantage of DA is that it is strategy-proof (Roth 1982, Dubins and Freedman 1981). A second advantage of DA is that it produces the stable matching that is most favorable to each student. Although its outcome is not necessarily Pareto efficient, it is constrained efficient among the stable mechanisms.

In many laboratory experiments testing DA, researchers find that it remains the mechanism that achieves the highest proportion of stable or envy-free allocations. Depending on the size of the match, the proportion of students revealing their preferences truthfully varies between 47% to over 80% (Hakimov and Kübler 2019). In addition to Boston and New York City, variants of DA have been implemented in Amsterdam, Hungary, Paris, New Orleans and Taiwan.

In the trade-off between elimination of justified envy and Pareto efficiency, DA gives up Pareto efficiency. The Top Trading Cycles mechanism (TTC), on the other hand, gives up elimination of justified envy, but is Pareto efficient. We now describe the TTC mechanism in its general form:

**Step 1:** Each student points to her favorite school. If there is no such school, she points to herself. Each school points to the applicant who has the highest priority at that school. There must be at least one cycle of students and schools pointing at each other or a student pointing to herself. Every student in a cycle is assigned to the school she is pointing to, or to herself. These students as well as their assignments are removed from the allocation process. School capacity is updated.

**Step k, k ≥ 2:** Each student again points to her favorite school among the schools that remain. Each school points to the applicant who has the highest priority among the remaining applicants. Every student in a cycle is assigned to the school she is pointing to, or to herself. These students as well as their assignments are removed from the allocation process. School capacity is updated.

The algorithm terminates when each student is assigned a school seat or all school seats are
assigned. The TTC mechanism is not only Pareto efficient, but also strategy-proof. In the lab, however, without prompting from the experimenters, sometime up to one-third of the subjects manipulate their preferences (Chen and Sönmez 2006).

In theory, TTC has an efficiency advantage over IA as well as DA: The outcome of IA is Pareto efficient provided that participants reveal their preferences truthfully. So any efficiency loss in IA is a consequence of preference manipulation. DA, on the other hand, is strategy-proof, but elimination of justified envy and Pareto efficiency are not compatible. Since DA Pareto dominates any other mechanism that eliminates justified envy, any efficiency loss in DA is a consequence of this incompatibility.

In practice, the only public school district which implemented TTC as its school choice mechanism is the New Orleans Recovery School District (RSD), in consultation with the Institute for Innovation in Public School Choice (Abdulkadiroğlu et al. 2017). However, one year after its implementation, the RSD switched to DA, citing the difficulty to explain TTC to parents as well as blocking pairs created by TTC as potentially subject to legal challenge as main reasons for the switch. Using data from New Orleans, Abdulkadiroğlu et al. (2017) find that the switch to DA had little impact on the overall aggregate rank distribution of choices received by applicants; however, no student is involved in a blocking pair as a result of the switch.

Lastly, in the fall of 2009, without the involvement of market design researchers, Chicago Public Schools decided to replace its highly manipulable matching algorithm for exam schools, a variant of IA, with a less manipulable mechanism, a capped version of the serial dictatorship (Pathak and Sönmez 2013).

In sum, market design in the school choice domain is considered a success story, with a large number of active research projects investigating school choice mechanisms around the world. While most existing research in this domain analyzes the static version of the school choice mechanisms, we notice dynamic variants of these mechanisms being implemented which provide information about others' behavior and allow students to revise their own applications upon observing others' actions. Examples include school choice in Amsterdam (de Haan et al. 2016) and Wake County, North Carolina (Dur et al. 2018). Theoretical analysis and experimental testing of the dynamic matching mechanisms remain open questions.

### 4.2 Re-design Centralized College Admissions Mechanisms

Like school choice, college admissions policies have been subject to debate and reform in many countries. In particular, many countries use centralized college admissions through standardized tests, including China, Greece, Hungary, Russia and Turkey. In what follows, we discuss the role of matching theory and experiments in the understanding the recent college admissions reforms in China.

In China, centralized matching processes via standardized tests assigning students to universities

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9 This section is mostly based on, and partly taken from Chen and Kesten (2017, 2019).
have been in place since 1952. The National College Entrance Examination, also known as *gaokao*, forms the foundation for the current college admissions system. In recent years, roughly 10 million high school seniors compete for 6 million seats at various Chinese universities each year. The matching of students to universities has profound implications for the education and labor market outcomes for these students. Through its regional variations and its evolution over time, the Chinese system also provides matching theorists and experimentalists with a wealth of field observations to enrich our understanding of matching mechanisms.

In recent years, each province implements an independent matching process from one of the two classes of mechanisms: the sequential or the parallel mechanism. The sequential mechanism, strategically equivalent to the Immediate Acceptance mechanism (IA), had been the only mechanism used in Chinese student assignments both at the high school and college level (Nie 2007b). However, this mechanism is not strategy-proof: “a good score in the college entrance exam is worth less than a good strategy in the ranking of colleges” (Nie 2007a).

To alleviate the problem of high-scoring students not being accepted by any universities, the *parallel mechanism* (PA) was first implemented in Hunan Province in 2001. In the parallel mechanism, students select several “parallel” colleges within each choice-band. For example, a student’s first choice-band may contain a set of three colleges, A, B, and C while her second choice-band may contain another set of three colleges, D, E, and F (in decreasing desirability within each band). Assignments for parallel colleges listed in the same band are considered temporary until all choices of that band have been considered. Thus, this mechanism lies between IA, where every choice is final, and DA, where every choice is temporary until all seats are filled.

By 2012, various versions of the parallel mechanism have been adopted by 28 out of 31 provinces. By 2019, all 31 provinces have abandoned the sequential in favor of various versions of the parallel mechanism differentiated by the number of parallel colleges within a choice-band, which is widely perceived to improve allocation outcomes for students.

To investigate the theoretical properties of the parallel mechanisms (PA), Chen and Kesten (2017) formulate a parametric family of application-rejection mechanisms where each member is characterized by some positive number \( e \in \{1, 2, \ldots, \infty\} \) of parallel and periodic choice-band sizes that allow the application and rejection process to continue before assignments are made permanent. As parameter \( e \) increases, we go from IA (\( e = 1 \)) to PA (\( e \in \{2, \infty\} \)), and from those to DA (\( e = \infty \)). They show that members of this family become “less manipulable” in the sense of Pathak and Sönmez (2013), and more stable as \( e \) increases. Specifically, the latter implies that, under truth-telling, when IA (resp. PA) selects a stable matching, then PA (resp. DA) also does so, but the converse statement is not true. This implies that all of the Chinese provinces that have adopted a parallel mechanism have transitioned to a less manipulable and more stable assignment system.

Furthermore, Chen and Kesten (2017) show that a parallel mechanism provides students with a certain sense of “insurance” by allowing them to list their equilibrium assignments under the IA mechanism as a safety option while listing more desirable options higher up in their preferences. This strategy leads to an outcome at least as good as that of the IA mechanism. Notably, such insurance
does not come at any *ex ante* welfare cost in a stylized setting.

To investigate behavioral responses to these mechanisms and to search for behavioral regularities where theory is silent, Chen and Kesten (2019) evaluate the sequential (IA), parallel (PA), and deferred acceptance (DA) mechanisms in the laboratory in two environments differentiated by their complexity. In the laboratory, participants are most likely to reveal their preferences truthfully under DA, followed by PA and then IA. Furthermore, while DA is significantly more stable than PA, which is more stable than IA, efficiency comparisons vary across environments. Whereas theory is silent about equilibrium selection, they find that stable Nash equilibrium outcomes are more likely to arise than unstable ones. Regardless of the metrics, the performance of PA is robustly sandwiched between IA and DA. Furthermore, 53% of the subjects adopt an insurance strategy under PA, making them at least as well off as what they could guarantee themselves under IA. These results help explain the recent reforms in Chinese school choice and college admissions.

In practice, we have observed changes within the parallel family. For example, Hunan Province pioneered the parallel mechanism in 2001 which allowed three parallel choices per choice-band. Later, it switched to a different parallel mechanism allowing five parallel choices per choice-band in 2010. Using admissions data from Hunan, Wei (2015) find that, by 2013, the new parallel mechanism \( (e = 5) \) is significant more stable than the old parallel mechanism \( (e = 3) \). In future studies, it would be desirable to pick more members to investigate the performance of different PA mechanisms.

Researchers have also examined other aspects of the Chinese college admissions mechanism, such as the timing of preference submission by students. Recent empirical and experimental studies such as Wu and Zhong (2014), Lien et al. (2016), and Jiang (2016) find that if students submit preferences before taking the exam, the measurement error in the exam can be corrected via IA, which leads to matchings that are stable with regard to students’ aptitudes.

In sum, there has been a fair amount of progress made in understanding and testing various aspects of centralized college admissions mechanisms. Because of the large number of choices available for centralized college admissions, it remains a challenge to design optimal matching mechanisms that simultaneously provide information to guide the application process and reduce the students’ cognitive load in preference reporting. Such information intervention policies start to emerge in the form of the dynamically adjusted admission cutoffs at each college during a prespecified time frame in the college admissions process in Inner Mongolia (Gong and Liang 2017) and Brazil (Bo and Hakimov *forthcoming*). While research analyzing existing information provision mechanisms in matching demonstrates that it improves the performance of these mechanisms compared to their static counterparts, it remains an open question what the optimal dynamic matching mechanisms might be.

**4.3 Improving Course Allocation Mechanisms**

Allocating course seats to students is a daunting task universities face every semester. It is a technically difficult problem in market design, as it involves assigning each student a package of indivisible goods among a large number of classes where some are substitutes and others are complements. To achieve
the goals of efficiency and equity, some business schools use preference-ranking mechanisms (revealed ordinal preferences) while others use variants of bidding systems (revealed cardinal preferences) in which students are given a fixed budget of tokens to bid on courses. In such bidding systems, bids serve the dual roles of inferring student preferences over courses and determining student priorities for courses.

Sönmez and Ünver (2010) present a theoretical analysis of course bidding, where they show that these dual roles may easily conflict. That is, preferences inferred from the bids might differ significantly from students’ true preferences. Furthermore, they propose the Gale-Shapley student-optimal stable mechanism (GS) that can be implemented by asking students for their preferences in addition to their bids over courses. The GS mechanism operates as follows:

*Step 1:* Each student is tentatively placed in her top three choices from her preference list. If a course has more students than its capacity, the lowest-bidding students for that course are dropped, so that each course tentatively holds no more students than its capacity.

*Step k, k ≥ 2:* Each student rejected from a course at step \( k - 1 \) is tentatively placed in her next choice course. Each course then tentatively retains those who have the highest bidding points among the new students as well as those tentatively retained at an earlier step. If a course holds more students than its capacity, the lowest-bidding students for that course are dropped, so that each course tentatively holds no more students than its capacity.

The algorithm terminates when no student is dropped from a course, or all options on the students’ preference list are exhausted. The tentative assignments become final.

To compare the new mechanism with the existing bidding system, Krishna and Ünver (2008) report, in *Management Science*, a field study complemented by a laboratory experiment at the Ross School of Business at the University of Michigan, which uses a course-bidding system. In this system, each student is endowed with a fixed budget of bidding points, which they can allocate among courses they are interested in. Students are then sorted in decreasing order by the points they place in a course, which generates a priority list. A serial dictatorship mechanism is executed in priority order, subject to course quota and feasibility constraints. The field study involves a personalized email sent to each student within a few hours of the official closure of course bidding. The email contains a list of all courses on which the student had placed bids in descending order of bid points and asks students to rank the courses. Their counterfactual analysis using GS concludes that a potential transition to GS is likely to lead to significant efficiency improvement: among the 489 students who submitted a rank-ordered list, 101 of them unambiguously prefer the GS mechanism while two strictly prefer the status quo. The others are indifferent. In a complementary lab experiment using the induced value method, the authors again find an improvement in efficiency under GS. Depending on the metric used, truthful preference revelation under GS is between \( 2/3 \) to 83%. Despite the evidence that switching to GS would improve the satisfaction level of many students, the Ross School of Business continues to use the course-bidding system.
A second example of course-bidding system is used by Harvard Business School. Budish and Cantillon (2012) document how it encouraged strategic behavior and often failed to produce efficient outcomes. To address these deficiencies, Budish (2011) proposes a new allocation mechanism that elicits from students their preferences over bundles of courses and uses these preferences to compute a price for each course that would form an approximate competitive equilibrium from equal income (A-CEEI). At these prices, each student receives her most preferred bundle of courses that she could afford. As the number of participants grows large, the amount of approximation as well as the incentives to misrepresent preferences would become small. The main advance of Budish (2011) compared to Sönmez and Ünver (2010) is to allow students to express preferences over bundles of courses rather than individual courses, thus capturing potential substitutability or complementarity among various courses.

To implement A-CEEI in practice, market designers need to deal with the issue of preference reporting over bundles of courses, which would be prohibitively large. A practical mechanism will necessarily use a simplified preference reporting language, which in turn raises the empirical question of how well the restricted preferences approximate true preferences. The Wharton Business School at the University of Pennsylvania implemented a simple version of A-CEEI, called Course Match (Budish et al. 2017) since 2013, replacing its old course-bidding system, the Wharton Auction.

In a forthcoming paper in Management Science, Budish and Kessler (2019) report a novel laboratory experiment that compares the performance of A-CEEI versus the existing Wharton Auction. There are several interesting features in the experiment design. For example, subjects are Wharton MBA students who have experience with the Wharton Auction, and who would be the future users of A-CEEI if it were adopted. Instead of endowing these subjects with artificially induced values (Smith 1982), they bring their real preferences into the lab. Specifically, subjects report preferences over a subset of courses to be offered the following semester, making it a realistic task. An innovation in the preference reporting language is the use of binary comparisons, in the form of “Do you prefer Schedule A or Schedule B?” which is cognitively simple compared to ranking over all possible schedules. They find that A-CEEI outperformed the incumbent Wharton Auction on measures of efficiency and fairness.

The experimental results helped persuade the Wharton committee to adopt A-CEEI and guide its practical implementation. The new mechanism is implemented as “Course Match.” Survey data suggest that A-CEEI has increased student satisfaction with their assigned schedule.

5 Labor Market

“A Father, being on the point of death, wished to be sure that his sons would give the same attention to his farm as he himself had given it. He called them to his bedside and said, “My sons, there is a great treasure hid in one of my vineyards.” The sons, after his death, took their spades and mattocks and carefully dug over every portion of their land. They found no treasure, but the vines repaid their labor by an extraordinary and superabundant crop.”

Aesop’s Fables

The labor market represents a rich assortment of opportunities for the scientist and manager to explore ways to improve existing conditions. Within economics, a myriad of research questions is
addressed by labor economists today, yet the bulk of work revolves around three bins: i) labor supply, ii) labor demand, and iii) the organization of labor markets and behavioral incentives therein. There is by now enough work in these three areas to fill at least a hundred factual tomes. In this section, we limit our attention to a subset of the third bin: exploring select recent work on the effects of market design and pecuniary incentives on worker behavior, and the interplay between pecuniary and non-pecuniary incentives (the interested reader should see List and Rasul (2014) for a discussion of the other two bins). We then explore challenges moving forward and our vision of the next set of frontiers.

A core feature of economics is that incentives matter. The key is to understand what sorts of incentives matter, and how, to individuals. While the role of pecuniary incentives within firms has been long studied in the sociology and management literatures, within economics the stream of work has its roots in contract theory. The basic questions for economists then revolve around how workers respond to incentives, and the optimal design of those incentives. Early empirical work used personnel data to measure the effects of compensation on individual productivity levels, but a difficult econometric challenge arose as most (all?) observed incentive contracts in naturally-occurring settings are endogenous, making causality difficult to establish. Economic experiments introduce exogeneity in incentives that are by design orthogonal to other management practices, opening the possibility of identifying the causal relationship between pecuniary incentives and effort levels of individual workers. We take this literature as a starting point to discuss work on how market design can be used to improve the workplace, with each of the bins showcased by laboratory and field experiments.

5.1 Leveraging behavioral economics to get more for your money in the workplace

Behavioral economics has become much more than academic curiosity. Today, organizations as distinct as governments and firms use behavioral insights to chart a particular course of action. While sister disciplines as varied as sociology, biology, and computer sciences have lent insights into the economic explorations, it is fair to say that to date psychology has made the deepest inroads in the behavioral economic revolution. This is due to the piercing nature of the received insights. For example, one of the deepest economic tenets—the basic independence assumption—has been under attack since the early experimental findings from the lab and field suggested that preferences are a function of current entitlements (see, e.g., Kahneman et al. 1990, List 2003). The most accepted theory explaining such behavior is broadly termed loss aversion.

One recent example leveraging loss aversion in the workplace is an 8-week long field experiment due to Hossain and List (2012). They explore whether worker productivity can be affected using simple loss averse framing of bonuses. In this manner, the treatment is particularly passive in comparison to previous field experiments that actually manipulated real endowments and explored choices (see, e.g., List 2004, 2011, Englemann and Hollard 2010). For instance, in the main treatments, workers in Hossain and List’s (2012) field experiment received letters in the mail announcing the treatment. In the clawback treatment, for example, rather than actually giving the employees the bonus money before the work week commenced, it was given provisionally, where the relevant portion of the letter read:
“for every week in which the weekly production average of your team is below 400 units/hour, the salary enhancement will be reduced by RMB 80...”

Alternatively, in the standard bonus treatment, the description read as follows:

“you will receive an RMB 80 bonus for every week the weekly production average of your team is above or equal to 400 units/hour...”

![Figure 4. Aggregate Differences in Per-Hour Productivities Under Punishment and Reward Treatments for Groups (reproduced from Hossain and List 2012)](image)

The Hossain and List (2012) setting was a Chinese manufacturing plant that produced consumer electronics. The treatments were performed over both individual and team production (the above passages are for the team setting). Hossain and List (2012) found that bonuses work: posed as either gains or losses, workers in both teams and individually increased productivity when they received a bonus. More importantly for our purposes, they also find that teams and individuals respond more to bonuses posed as losses than as comparable bonuses posed as gains. Figure 4 summarizes empirical results from the 6 team sets in the field experiment of Hossain and List (2012). Importantly, Figure 4 shows that in 5 of 6 sets the clawback treatment outperformed the standard bonus treatment. Overall, team productivity is increased by 1% purely due to the framing manipulation. Comparable effects from the individual treatments, reported in the bottom panel of Figure 4, are of the same sign but are not statistically significantly different to each other. While Figure 4 does not reveal the temporal treatment trends in the data, importantly when considering the treatment effects over time, the incentive effect does not wane: over the six-month study period the loss averse effects remain in the data. Furthermore, these productivity enhancements do not come with concomitant negative effects on the quality of work as measured by defect rates.

Subsequent work has largely replicated these results (see, e.g., Fryer et al. 2012, Levitt et al. 2016, Imas et al. 2017, and Bulte et al. 2019). Similar to Hossain and List (2012), the main innovation in this literature is that agents receive an up-front payment which they have to return in case their productivity or output fails to meet a certain threshold (i.e., a bonus scheme with up-front payments).
Fryer et al. (2012), for example, provide pecuniary incentives to grammar and high school teachers to increase productivity as measured by the performance of their students. While standard bonuses fail to increase teacher performance, leveraging the clawback scheme is quite effective.\textsuperscript{10}

On a practical note, these examples highlight the interplay between pecuniary and non-pecuniary aspects of compensation in that this set of results shows that conditional on bonuses being provided, framing matters. Given that framing can be adjusted costlessly, these approaches are simple ways in which firms can deepen the effects of pecuniary incentives. Theoretically, these results from the field provide an example consonant with loss aversion in a natural labor market setting. As such, the results provide concrete evidence of the generalizability of such insights from laboratory evidence, and provide a natural example highlighting the complementarity of lab and field experiments.

5.2 Putting market design to work to increase effort in the workplace

“Luck is the residue of design.”
Milton (1628)

While designing individual incentive schemes, such as clawback bonus contracts, have proven quite fruitful, market design comes in many flavors. One such example is rewarding employees based on relative payoffs (tournaments), which are ubiquitous in the workplace. Job promotions, earning bonuses, employee of the month, and the like all revolve around relative assessment of workers. The literature on the market design of tournaments has witnessed deep contributions theoretically, showcasing the benefits and costs of relative performance incentives (see e.g., Lazear and Rosen 1981, Holmstrom 1982). Yet, empirically testing the theoretical predictions has proven quite difficult, as observing individual effort, the main outcome variable in the theory, has been elusive in field settings.

One focus, therefore, has been to use laboratory experiments that are able to measure effort directly. An early experiment in this spirit is due to Bull et al. (1987). They design a lab experiment with student subjects to explore the first order predictions from tournament models concerning effort provision. In practice, the object of choice in the experiment is asking the student to circle a number that represents their “effort” choice, with higher numbers yielding a better chance of winning, but being more costly in a convex manner. This effort choice is then added to an idiosyncratic shock, or “luck” component, that is uniformly distributed, and their sum determines the tournament outcome.

This approach, importantly and cleverly, embeds the essential elements of the tournament theory in the effort choice setting. Bull et al. (1987) find that while there is considerable noise in individual play, effort levels converge to theoretical predictions in aggregate. That is, while individual effort level

\textsuperscript{10} Further evidence for the importance of loss aversion in the design of compensations schemes in field settings is provided by Ockenfels et al. (2014), who study the bonus scheme of a multinational company. The bonus scheme created a clear reference point as managers in parts of the company learned not only the size of their bonus but also the percentage share of their bonus relative to their direct colleagues. Studying the association between these bonus shares and job satisfaction, Ockenfels et al. find a substantial asymmetry around this 100% threshold – well in line with the patterns predicted by loss aversion.
choices in the lab are quite noisily distributed around the equilibrium prediction, in aggregate the theory performs remarkably well. A key win for the theory.

Building on this seminal work, List et al. (2019) use complementary lab and field experiments to not only explore equilibrium play, but to analyze whether the number of competitors, or the size of tournament, affects effort levels. In the previous literature, the key assumption that the luck term is drawn from a uniform distribution makes this particular question moot when workers are risk neutral, because the number of entrants in this case does not affect equilibrium effort levels. Yet, there are several instances where such an assumption need not hold. Indeed, in important ways, endogenizing the number of players allowed to enter the tournament becomes an interesting market design consideration, as was seemingly anticipated by the English poet Milton (1628), who once quipped that luck is the residue of design.

Consider the thought experiment of a worker innovating on the job with one prize awarded to the best innovator. Suppose that there are many potentially successful innovation paths, and workers arbitrarily choose a path. Each worker then expects to be a successful innovator, but she also expects that at least one other worker will be successful too. Hence, effort is crucial in determining the winning innovator, and investment is high—and even higher if the number of competitors expands. Alternatively, suppose that workers believe the chance of developing a very successful product are small. In that case, they expect that luck will play a crucial role in selecting the winner. If there are many innovators, each worker knows that at least one of them will be lucky, but also knows that it is unlikely that it will be them. Since luck is much more important in selecting the winner than effort in this case, workers invest little effort, instead relying on luck to determine the winner. This result is exacerbated as the number of competitors increases, leading to an even lower level of investment as the number of competitors increases. Several real-world examples abound, from development of autonomous vehicles to finding medicinal drug breakthroughs.

The List et al. (2019) theory highlights these intuitions and shows that if the distribution of the uncertainty component is skewed, the number of competitors allowed in the competition has a critical influence on equilibrium effort levels. As the number of competitors increases, a worker’s equilibrium effort level (i) decreases if there is small mass on good luck, (ii) remains constant if the luck component is drawn from a uniform density, and (iii) increases if there is a large mass on good luck. The intuition is that the marginal benefit from committing effort depends on both the number of competitors and on the good draw mass, which depends critically on the density function’s slope.

List et al.’s (2019) empirical approach to test the theory begins in the laboratory and closely follows Bull et al.’s (1987) approach. This permits a study of labor markets that differ only in the shape of the density function, allowing a unique insight into whether changes in the component’s shape itself can lead to predicted behavioral changes. Their second empirical approach is to use a field experiment that resembles the important features of the theory, but maintains enough control to allow a formal test.

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In a set of innovative papers, Boudreau et al. (2011, 2013) examine naturally-occurring data to explore the effects of group sizes in tournaments on software development. Their variable of interest is the score assigned to a solution of a software problem rather than effort levels. See also Orrison et al.’s (2004) experimental work.
of the theory. In doing so, it is important to create an experimental design that exogenously varies their major treatment variable—number of competitors—in an environment that permits an understanding of the other important features of the situation.

This is not simple because one needs to find a naturally-occurring environment where the random stochastic component takes a shape that is well understood by the participants. List et al. (2019) ended up choosing recreational commercial fisherman, where the private ponds were stocked with rainbow trout or salmon trout. Importantly, the fishing pond permits a natural test of the theory for the case of a decreasing density function. This is because of the fish schooling: the density function of ‘luck’ is decreasing since schools never cover more than just a few rectangles of where the competitors are placed, and hence the amount of mass on having good luck is quite small.

Overall, the lab results are in line with the tournament theory. Most importantly, they report that when exploring tournaments with 2, 3, and 4 players, the impact of group size on effort is consonant with theory. The field experimental results complement these insights by providing evidence consonant with the theory within a special case of the theory—when the density function is negatively skewed. In this case, the author’s report evidence that adding competitors decreases individual effort levels especially when they control for fatigue.

Beyond testing theory, the received results enhance the manager’s choice set by showing that the number of competitors in a relative pay incentive scheme has important effects on individual effort levels. Methodologically, the study showcases the power of testing the theory using complementary lab and field experiments within the same study (rather than across studies as shown in the loss aversion experiments). First using an artificial setting that permits an examination of markets that differ only in the shape of the density function, allows a test of such effects that would be difficult to identify in naturally-occurring data. Pairing that with a second empirical approach that maintains randomization, and closely resembles the important features of the theory, as a field test provides much stronger inference of the underlying data patterns than either the lab or field approach could provide in isolation.

5.3 Understanding non-pecuniary incentives in the workplace: from gift exchange to CSR

Perhaps the least understood aspect of the designer’s quiver is how non-pecuniary incentives work in labor markets. Yet, recent literature is beginning to shed insights into this fascinating area. A few examples include Bradler et al. (2016) and Gallus (2017), who use field experiments to explore the power of employee recognition on employee performance. The results are impressive, as for example the Wikipedia natural field experiment of Gallus (2017) shows that her awards have a sizeable effect on newcomer retention, which persists over a span of four quarters. Likewise, Cohn et al. (2014) reveal how the perceptions of the fairness of pay affects effort provision.

Relatedly, field experimental research into unconditional gifts in the workplace is a burgeoning area of research—see Gneezy and List’s (2006) surprise pay raises, pay cuts in Kube et al. (2013), and in-kind gifts in Kube et al. (2012). And, recent work on corporate social responsibility (CSR) highlights
that gifts for the social good can also have important labor market effects (see, e.g., List and Momeni 2019; Tonin and Vlassopoulos 2014). In this subsection, we focus attention to these two strands of research: gift exchange and CSR.

**Gift Exchange**

A common result that is found in large data sets is that employers are observed paying above the market equilibrium wage. And, when effort is monitored, workers exert more than the minimum effort level. This empirical observation has induced a set of economic models based on the assumption of their being a positive relationship between worker wages and effort levels (Akerlof 1982, Akerlof and Yellen 1990). The equilibrium of these models is for employers to offer higher than market clearing wages, and workers to reciprocate with high effort levels, making the situation a win-win.

Within experimental economics, the literature on social preferences has become one of the most influential areas of research (see, e.g., Camerer and Weigelt 1988, Fehr et al. 1993, Levitt and List 2007). Findings from such games have been interpreted as providing strong evidence that many agents behave in a reciprocal manner even when the behavior is costly and yields neither present nor future material rewards. Further, the results have been widely applied outside the laboratory, becoming a descriptor of environments far removed from the domains of data generation. An early study exploring the importance of gift exchange in a naturally-occurring market is List (2006), who used a series of field experiments in a product market to show that inference from these early games should be made with care since the environment might engender certain behaviors, and that strategic reciprocity might masquerade as social preferences in certain instances.

Gneezy and List (2006) took this notion to the workplace by exploring the effects of gift exchange on worker productivity. They use two natural field experiments to explore gift-exchange in the workplace. In the first they recruited undergraduate students to participate in computerizing the holdings of a small library at the University of Chicago. In the no-Gift treatment, individuals were offered a flat wage of $12 per hour. In the Gift treatment, once the task was explained to participants, they were surprisingly paid $20 per hour rather than $12 per hour as advertised. The second field experiment was part of a door to door fundraising drive to support a university research center in North Carolina. Fundraising solicitors were recruited and told they would be paid $10 per hour, and those in the Gift treatment were surprisingly told they would receive $20 per hour.
The main results from the Library task are summarized in Figure 5. Two stark patterns are revealed in Figure 5. First, in line with earlier evidence from the lab, there are signs of significant gift exchange in the first few hours of the task. Second, there is a significant decrease in the gift exchange effect after a few hours, with no significant differences existing over a longer period. Importantly, the data reveal how the gift worked early on to induce higher output, but overall the results show that with the same budget, the employer would have been better off paying market wages.12

Since this early work, the evidence on the efficacy of gift exchange in the workplace has come in various forms. Kube et al. (2012) find similar short run effect sizes as Gneezy and List (2006) using an in-kind gift. Likewise, using a negative wage gift, Kube et al. (2013) find a similarly large treatment effect when considering decreases in productivity. Alternatively, there are studies that report small and statistically weak gift exchange effects. For instance, Al-Ubaydli et al. (2015) report small effects despite of the fact that gifts used in their study were large—paying unskilled workers $18/hr to pack envelopes. In an effort to reconcile the various facts around gift exchange in the workplace, Esteves-Sorenson (2017) carefully identifies several factors that could be underlying the inconsistent results. She concludes that “after dealing with all these confounds, our field test results are most consistent with a standard model: workers did not increase effort in response to fixed wage raises but did do so in response to a piece rate scheme.” In this way, her results are quite consonant with the long-term estimates from Gneezy and List (2006). We return to the important question of inference from this body of work at the end of this section.

12 Building on Gneezy and List (2006), Ockenfels, Sliwka, and Werner (2015) and Sliwka and Werner (2017) have explored the timing of wage increases in more detail showing that performance can be raised when providing smaller but more frequent wage increases. As Sliwka and Werner argue, these patterns (as well as the pattern detected by Gneezy and List) can be well-organized in a simple dynamic model of reciprocity, where workers reciprocate higher wages, but adapt their reference points over time. In turn, reciprocal reactions to wage increases naturally wear off, but can be made more persistent when the wages are increased gradually.
The role of corporate social responsibility (CSR) has been debated at least since Friedman famously described CSR as a “fundamentally subversive doctrine” in a 1970 NY Times article. And, in his usual combative style Friedman described contrarians to his views on CSR as “puppets of the intellectual forces that have been undermining the basis of a free society.” In this regard, the world has certainly turned its cheek to Friedman’s advice, as today over 90% of major businesses have specific programs dedicated to CSR. Yet, is this transformation a sign that the CSR business is a good business?

For their part, researchers have explored the efficacy of CSR in various venues. Broadly, most studies have focused on the demand side of the market, examining whether consumers are moved by the CSR programs of firms. Alternatively, only until recently has work begun to focus on the supply side to determine whether employees are affected by CSR. In this spirit, the notion of examining the supply side resembles gift exchange, except in this case workers reciprocate higher effort when the firm does good for the society at large rather than for themselves directly.

Defined narrowly, thus far there exists little consensus on whether CSR investments positively impact the bottom line. While some studies report a positive effect (Waddock and Graves 1997), others find mixed effects (see, e.g., Servaes and Tamayo 2013). As aforementioned, however, one possible reason for these mixed findings is that with few exceptions, empirical studies of CSR tend to focus primarily on the demand side of the market (e.g., Du et al. 2011).

In a study forthcoming in Management Science, List and Momeni (2019) address this shortcoming in the literature by exploring the supply side effects of CSR within an on-line marketplace, with a particular emphasis placed on observing misbehaviors in the workplace. List and Momeni (2019) operationalized a test of CSR by conducting a natural field experiment using workers from Amazon’s Mechanical Turk (MTurk). This approach has become a common one in the economics community searching for convenience labor market samples, as MTurk is an online labor market platform where ads are made to available workers. List and Momeni (2019) try to hire workers who land on their website after seeing an advertisement for work. Upon landing on their website, potential workers were randomized into one of the 6 treatments that had different wages and CSR language. In terms of the basic contracts, people were told that 10% of the total wage would be paid to workers upfront and the remaining 90% would be paid after they completed the task. Accepting the contract without completing the task is one of two measures they use for worker misbehavior (since the worker is paid without delivery).

The task was for each worker to transcribe 10 images of short German texts, scanned from old German books. On average, each image was composed of around 30 words or 183 characters. The authors used German texts to make the task harder and less enjoyable. Workers who submitted all 10 images received the full wage specified in the contract. Before starting to work on any given image,
workers were required to report if the image was legible. If an image was reported as unreadable, the worker skipped that image and moved on to the next, yet still received full pay. The second misbehavior naturally arises: misreporting perfectly readable images as unreadable to avoid costly transcription was their second measure of misbehavior.

While List and Momeni (2019) had 6 treatment conditions, the main treatment comparisons for our purposes were the outcomes of the baseline and a CSR treatment that had advertisement that was identical to the baseline except included a CSR message:

*Our firm is committed to give back in meaningful ways. We are passionate about encouraging education for the next generation. We do our part by donating money to influential non-profit organizations that support education for children from low socioeconomic backgrounds. In keeping with our philanthropic mission, we donate the equivalent of x% of our wage bill in cash (on behalf of all workers who help us with this project) to UNICEF Education Programs. UNICEF works tirelessly to ensure that every child regardless of gender, ethnicity or circumstances has access to a quality education. You may find out more about UNICEF Education Programs at: UNICEF.*

The reported treatment effects are interesting, but one stark set of results stands out: the firm’s use of CSR increased worker misbehavior. More specifically, workers who received a CSR message were more likely to become cheaters and cheated more often than those who were not incentivized with CSR. The data pattern is consistent with a “moral-licensing” impact: doing good on one dimension (CSR work) allows the worker to shirk on another (misbehaving). Such an impact was anticipated by Benabou and Tirole (2010), who note that “people who have recently done good in one dimension may feel immunized against negative (social or self ) inferences, and thus later on act less morally constrained.” As a whole, the results raise the potential that while CSR could very well have positive selection effects, there is a dark side of CSR that should be understood. More work is necessary.

5.4 Generation next: welfare, structural models, and opening the black box of the firm

In summarizing the range of work discussed in this section, several issues might have arisen to the astute reader. Early on, one might have asked while these clawback incentives in Hossain and List (2012) are neat, would any worker actually like them in practice? That is, would the firm implementing such incentives soon find itself employee-less? Or, perhaps less extreme, maybe workers will remain in the firm but be miserable. Likewise, in considering the effects of gift exchange, one might wonder if the underlying motivations at work for the higher effort observed are due to altruism, warm glow, reciprocity, or some other consideration. Furthermore, in terms of market design choices, the reader might have wondered how CSR incentives affect other aspects of sorting, such as whether more productive workers prefer to be employed by firms that have a viable CSR program in place. Do workers view CSR like other workplace amenities, and what are the overall welfare effects of CSR?

These, and related questions, are important challenges that future work should take on, but the approach need not be blind, as some first steps have started to tackle these challenges. For example, one natural question that arises when the literature produces an incentive regime that improves
performance, is whether such a mechanism can be viewed as improving overall welfare levels. Considering the clawback scheme that leverages worker loss aversion, the evidence in Imas et al. (2016) and Bulte et al. (2019) suggests that workers value the clawback as a commitment device, and therefore reciprocate by improving their performance in subsequent interactions. This result suggests that firms will not invoke anger or lose their employees. Of course, more work is necessary to be sure of such preliminary results, but this gives some sense of optimism that the loss aversion nudge will push workers to other firms. In this way, a call for future research is to identify the overall welfare effects of nudges.

In terms of future research paths on gift exchange literature, there is little field evidence about the nature of the observed social preferences towards employers. For instance, are workers acting on purely altruistic motives, as in Becker (1974). Perhaps instead, workers are reacting to their warm glow, in the spirit of Andreoni (1989). Or, perhaps the actual model at work is the original gift exchange view of Akerlof (1982). The importance of parsing these underpinnings is not just academic curiosity, as key market design considerations critically rely on whether extra worker effort is due to enhanced value to the employer, pure value to self, or are strategically reciprocal in nature. Yet, there are many challenges to parsing such models.

In this case a structural model combined with field experimental variation can provide insights. This is exactly the roadmap provided by DellaVigna et al. (2016), who combine a structural model with a closely-linked field experiment to explore the lessons learned from the literature. What immediately falls out of such an exercise is that the extant literature lacks the key design features to parse the various interpretations. In particular, two elements are missing from the designs in the literature: i) there is no specification of the value to the employer of the worker’s effort, and ii) a key unobservable is the cost of effort.

DellaVigna et al. (2016) design a field experiment to address both issues, yielding insights into the underlying primitives of workers. Their data and theoretical framework suggests that the warm glow model is key in explaining the received data in their setting. Importantly, such insights would have been difficult to obtain without the theoretical/experimental link offered in the study to permit a firmer understanding of the forces at work.

Hedblom et al. (2019) provide a similar contribution to the CSR literature, where they combine a structural approach with a natural field experiment to consider how CSR affects sorting into the workplace. Using data from more than 1000 job seekers, they report strong evidence on the efficacy of CSR: it attracts employees who are more productive, produce higher quality work, and have more highly valued leisure time. In terms of enhancing the labor pool, use of CSR increases the number of applicants by 25 percent, an impact comparable to the effect of a 36 percent increase in wages. This work balances the moral hazard effects reported in List and Momeni (2019) and showcases the key complementarities in CSR and pecuniary incentives. In addition, this work provides compelling reasons for why firms might create and actively engage in CSR activities. We view these two examples as representing a key call for future work that combines the structural and field experimental approaches to shed new insights into both old and new areas of study.
This line of work underscores the import of leveraging firms and opening the black box of the firm. As Levitt and List (2009) discuss, there have been three distinct waves of field experimental research in economics. We are currently in the third wave, which has brought a deeper and broader exploration of economic phenomena in organizations. Within this generation of field experiments, an attractive approach is creating partnerships with private entities. Low hanging fruit remain in the areas of optimal worker incentive schemes, workplace design, wellness and health programs, and a several related topics in the black box of the firm. One such area in the black box relates to a longstanding puzzle in economics: the striking differences in firm-level productivity across space and time. With total factor productivity ratios in the neighborhood of 3:1 across high productivity and low productivity (90th percentile to 10th percentile) firms, understanding their sources is of first order import. One such line of work considers management practice. Recently, a rich literature has developed that provides key evidence around management’s role in such disparities (see, e.g., Bloom and Van Reenen 2007, 2011, Gosnell et al. 2019). Yet, much work remains, and we envisage an active area for future work for decades to come.

6 Concluding Remarks

“The proof of the pudding is in the eating.”

Cervantes in his Don Quixote (1605)

In the last few decades, Management Science has published foundational work in market design and human behavior, as outlined in our introduction. Today, economists, computer scientists, operations researchers, managers and others are increasingly asked to design mechanisms for markets and organizations. Many of the applications are motivated by failures of incentives in markets and organizations, and the urgent need to understand and fix the design flaws. One lesson learned from these efforts, as selectively surveyed in our article, is that institutional details matter. Even small changes in the rules can have a dramatic impact on the effectiveness and efficiency of a market. For instance, whether an otherwise identical auction ends with a hard or a soft close can significantly affect bidding, revenues, and allocative efficiency. Market design forces researchers to pay attention to details that might otherwise be overlooked. Our survey illustrates how the practical lessons from market design activities in various contexts may accumulate to become broad and sound scientific knowledge, which in turn promotes better and more reliable markets and organizations.

Some critics sometimes complain that economic theory is too disconnected from practical problems. However, in all cases that we survey, game theory proved helpful to develop intuition and to address real-life challenges. That said, market design may require decisions that are beyond current knowledge. Part of the reason is that theory must abstract from institutional and behavioral real-world complexities. For instance, people often follow their own – bounded – rationality, characterized by limitations of motivation, cognition and adaptation. Boundedly rational agents only have limited cognitive abilities and bounded willpower, which constrains optimally responding to auction and matching mechanisms (e.g., Hassidim 2019, Engelbrecht-Wiggans and Katok 2008,
Ockenfels and Selten 2005). Bounded self-interest implies that humans are often willing to sacrifice their own interests to help others, which is key for understanding how to engineer trust in the sharing economy (see Section 3). This is why practical market design is often fruitfully complemented by lab and field experiments that test game theory’s predictions and provide a testbed and proof of concept before introducing new mechanisms into operating markets. A mechanism that works fine under simplifying assumptions about human behavior may fail under descriptively more relevant assumptions.

Our survey includes discussion of where we find gaps in our knowledge and where we believe more research is promising for auction, matching, feedback, and labor market design, respectively. There are also more general insights that hold across market design domains. In some cases, for instance, markets with theoretically attractive properties involve transactions that are perceived by many as repugnant. This can be an important constraint on market design. For instance, buying and selling kidneys for transplantation or trading school and university admission is illegal in most countries (Roth 2007). Thus, a stream of recent studies is concerned with understanding the empirical nature and robustness of such constraints, in an attempt to reconcile ethical concerns with economic effectiveness (e.g., Ambuehl 2017, Ambuehl et al. 2015, 2019a,b, Leider and Roth 2010, Kirchler et al. 2016).

Many opportunities and challenges in market design have to do with recent advances in computer and communication technology, which often allow for radical innovation in market design. Indeed, smart markets are popping up everywhere, from new kidney exchanges, dating, job and ride hailing markets, ad and spectrum auctions, to innovative climate, electricity and financial markets. The development of these markets not only creates new business opportunities to benefit our social and economic lives, but also improve our scientific understanding of engineering incentives and markets. There is probably no other field in economics and management science, where researchers and practitioners gain so much by carefully listening to and working with one another. In this spirit, perhaps the most foundational change for generation of knowledge is that researchers will increasingly have to use the HOV lane in their own work, for riding alone will soon be an inefficient choice in the knowledge production game.

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