Personal Statement

For Evaluation for Promotion to Associate Professor with Tenure

Sergei Glebkin
Assistant Professor of Finance, INSEAD

January 2024

Contents

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CONTACT INFORMATION

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EMPLOYMENT

INSEAD, Assistant Professor of Finance, 2016–present

AFFILIATIONS

CEPR, research affiliate from January 2024
Finance Theory Group, member from May 2022

EDUCATION

London School of Economics, PhD in Finance, 2016
New Economic School, MA in Economics, 2011
Moscow State University, MSc (BSc) in Physics, 2010 (2008)

RESEARCH INTERESTS

Asset Pricing in Imperfect Markets, Information Economics, Market Microstructure

PUBLICATIONS

1. Sergei Glebkin, Naveen Gondhi, and John Chi-Fong Kuong, Funding Constraints and Informational Efficiency, **Review of Financial Studies**, 2021.

2. Sergei Glebkin, Bart Zhou Yueshen, and Ji Shen, Simultaneous Multilateral Search, **Review of Financial Studies**, 2023.

3. Sergei Glebkin, Semyon Malamud, and Alberto Teguia, Illiquidity and Higher Cumulants, **Review of Financial Studies**, 2023.

4. Sergei Glebkin and John Chi-Fong Kuong, When Large Traders Create Noise, **Journal of Financial Economics**, 2023.

WORKING PAPERS

5. Florent Gallien, Sergei Glebkin, Serge Kassibrakis, Semyon Malamud, and Alberto Teguia, Price Formation in the Foreign Exchange Market, reject and resubmit at the **Journal of Financial Economics**, resubmitted.

6. Efstathios Avdis and Sergei Glebkin, CHILE, finalizing for submission at the **Journal of Finance**.

7. Sergei Glebkin, Semyon Malamud, and Alberto Teguia, Strategic Trading with Wealth Effects.

CONFERENCE PRESENTATIONS & INVITED SEMINARS:

*Invited seminars are highlighted in **bold**; c=conference presentations by co-authors; x=conference canceled due to COVID-19. Conference discussions are listed separately.*

2024: American Finance Association Meeting

2023: **University of Essex, University of South Florida,** LTI Asset Pricing Conference in Turin, INSEAD Finance Symposium, Finance Theory Group Meeting at UW-Madison, Finance Theory Group Meeting at Michigan Ross (short session, c), Western Finance Association Meeting (c)

2022: NES 30th Anniversary Conference, American Finance Association Meeting (c)

2021: **École Polytechnique Fédérale de Lausanne, Collegio Carlo Alberto**

<u>2020:</u> American Finance Association Meeting, Financial Intermediation Research Society Meeting, Texas Finance Festival (x), Society for Financial Studies Cavalcade Conference (c), Western Finance Association Meeting (c)

<u>2019:</u> Financial Intermediation Research Society Meeting, Finance Theory Group European Meeting in Madrid, Paris December Meeting, Wellington Finance Summit (c)

<u>2018:</u> **Alberta School of Business,** HEC-McGill Winter Finance Workshop, European Finance Association Meeting, INSEAD Finance Symposium, Adam Smith Workshop (c), Western Finance Association Meeting (c), European Capital Markets Workshop (c), Frontiers of Finance (c), Tel Aviv University Finance Conference (c)

<u>2017:</u> European Winter Finance Summit, Paul Woolley Centre Conference, Finance Theory Group European Meeting in London (short session), INSEAD Finance Symposium, Western Finance Association Meeting, NES 25th Anniversary Conference

<u>2016:</u> **University of Toronto (Economics), HEC Montreal, McGill, INSEAD, Northwestern Kellogg,** Society for Financial Studies Cavalcade Conference, Northern Finance Association Meeting

<u>2015:</u> Econometric Society World Congress

<u>2014:</u> LBS Trans-Atlantic Doctoral Conference, Econometric Society European Meeting

<u>2013:</u> Annual Meeting of European Financial Management Association

Conference Discussions

Market Power in the Securities Lending Market, by Shuaiyu Chen, Ron Kaniel, and Christian C. Opp, 2023 Society for Financial Studies Cavalcade Conference.

Price Discovery for Derivatives, by Christian Keller and Michael Tseng, 2023 HEC-McGill Winter Finance Workshop.

A Long and a Short Leg Make For a Wobbly Equilibrium, by Nicolae Garleanu, Stavros Panageas, and Geoffery Zheng, 2023 INSEAD Finance Symposium.

How Competitive is the Stock Market?, by Valentin Haddad, Paul Huebner, and Erik Loualiche, 2022 HEC-CEPR conference.

The Impossibility of Krusell-Smith Equilibria, by Tobias Broer, Alexandre N. Kohlhas, Kurt Mitman, and Kathrin Schlafmann, 2021 JEDC Conference on Markets and Economies with Information Frictions.

Benchmarking Intensity, by Anna Pavlova and Taisiya Sikorskaya, 2021 INSEAD Finance Symposium.

Market Feedback: Who Learns What?, by Itay Goldstein, Jan Schneemeier, and Liyan Yang, 2020 INSEAD Finance Symposium.

Carrot and Stick: A Risk-Sharing Rationale for Fulcrum Fees in Active Fund Management, by Juan Sotes-Paladino and Fernando Zapatero, 2020 Paris Dauphine Hedge Fund Research Conference.

Inventory Management, Dealers' Connections, and Prices in OTC Markets, by Jean-Edouard Colliard, Thierry Foucault, and Peter Hoffmann, 2019 Erasmus Liquidity Conference.

Up-Cascaded Wisdom of the Crowd, by Lin William Cong and Yizhou Xiao, 2018 European Finance Association Meeting.

Private Information, Securities Lending, and Asset Prices, by Mahdi Nezafat and Mark Schroder, 2018 European Finance Association Meeting.

Dynamic Liquidity-Based Security Design, by Emre Ozdenoren, Kathy Yuan, and Shengxing Zhang, 2018 INSEAD Finance Symposium.

The Value of Performance Signals Under Contracting Constraints, by Pierre Chaigneau and Alex Edmans, 2017 Northern Finance Association Meeting.

Information, Imperfect Competition, and Volatility, by Mahdi Nezafat and Mark Schroder, 2016 European Finance Association Meeting.

Awards and Grants

Grant from Europlace Institute of Finance for research on price formation in the foreign exchange market (in collaboration with Semyon Malamud and Alberto Teguia), 2023

INSEAD **Dean's Commendation for Excellence in MBA Teaching**, 2021

PhD Mentoring

Advisor of Nikola Kiprijanovski (ongoing)

Member of dissertation committee of Dima Pugachev (INSEAD PhD 2023, placed at Norwegian School of Economics) and Dmitry Chebotarev (INSEAD PhD 2022, Placed at Indiana Kelley)

External examiner of Etienne Borocco (Paris Dauphine PhD 2019)

Refereeing

American Economic Review, Econometrica, Review of Economic Studies, Journal of Finance, Review of Financial Studies, Journal of Financial Economics, Journal of Economic Theory, AEJ: Micro, Management Science, Review of Asset Pricing Studies, Journal of Financial and Quantitative Analysis, Mathematics and Financial Economics, Journal of Economic Dynamics and Control

Program Committees

European Economic Association, 2023–present
Northern Finance Association, 2017–present

Teaching and Pedagogical Material Development

Corporate Financial Policy (MBA), INSEAD, 2017–present
Continuous Time Finance (PhD), INSEAD, 2018–present

Wrote the case **"Square Inc's Valuation in 2014"** with Lily Fang and John Kuong

Developed the simulation **"Trading Games and Arbitrage Pricing"** with Junyuan Zou

Media Mentions

Bloomberg, 5 September 2017, "Lots of Liquidity Isn't Always Better"

Additional Information

Languages: Russian (native), English (fluent), French (intermediate)
Personal: Married, three kids, ages 2, 6, and 10

Last updated: November 2023

II Research statement

I am a financial economist working in the field of asset pricing in imperfect markets. By perfect markets, I mean those that are *centralized*, feature *perfect competition*, *no information asymmetries*, and *no financial constraints*. Imperfect markets are those that do not meet at least one of these criteria. My research focuses on the implications of market imperfections for asset prices and different aspects of market quality (information efficiency, liquidity, and welfare). It demonstrates that these implications often depend crucially on both the degree and the type of imperfections. For example, more competition can be beneficial in some markets, but it can have unintended consequences in other markets.[1] Paraphrasing Leo Tolstoy: All perfect markets are alike; each imperfect market is imperfect in its own way.[2]

My research is primarily theoretical, but I also use data to motivate the research questions and to test my theories. While all of my papers are concerned with the effects of various market imperfections on asset prices and market quality, they can further be grouped into four more granular, overlapping research streams. These streams, as well as the distribution of my papers across them, are described below. In the sequel, [N] refers to the corresponding paper number in my CV.[3]

- *Wealth effects and market quality.* The distribution of wealth across different market participants has important implications for liquidity and information efficiency. The amount of wealth affects investors' willingness to take risks. It might also have the additional effect of relaxing their constraints. In [1], we investigate the effects of wealth on informational efficiency via the constraints channel. Focusing on the risk tolerance channel, we investigate the effects of wealth on liquidity in [7] and on both liquidity and information efficiency in [6].

- *Amplification of shocks and financial fragility.* The interaction of several imperfections can generate strategic complementarities, whereby the actions of different market participants reinforce each other. Complementarities, in turn, are associated with the amplification of shocks and fragility, i.e., a situation in which a small shock

[1] See [4], or its description in Section B.

[2] The opening line of Leo Tolstoy's novel Anna Karenina is: "All happy families are alike; each unhappy family is unhappy in its own way." The economics tradition of using this paraphrase goes back to at least Lucas (1989): "Complete market economies are all alike, but each incomplete market economy is incomplete in its own individual way." See also Weill (2020): "All centralized markets are the same, but each OTC market is unique in its own way."

[3] The list of my papers is also available separately in Section H.

disproportionately affects a market. My co-authors and I identified two such mechanisms based on the interaction of financial constraints with asymmetric information ([1]) and of market power with asymmetric information ([4]).

- *Decentralized markets.* In the traditional models of over-the-counter (OTC) markets, the terms of trade are determined *bilaterally* between a customer and a dealer. In contrast, centralized market models entail *all-to-all* trading in a single marketplace. Real-life markets often deviate from these models, neither being strictly bilateral nor all-to-all. My research on decentralized markets focuses on these "intermediate" market types. For instance, in some markets like corporate bonds, *one-to-many* matching occurs on electronic platforms, allowing customers to request quotes from multiple dealers simultaneously. In [2], we explore the effects of such platforms. Additionally, markets like foreign exchange exhibit a *two-tiered* structure, merging centralized and OTC segments. In [5], we investigate the interplay between the OTC (dealer-to-customer) and centralized (dealer-to-dealer) segments of the foreign exchange market, both theoretically and empirically.

- *Generalizing CARA-Normal framework.* Many of my papers consider asset markets with imperfect competition and/or asymmetric information. The standard framework for studying such markets assumes normally distributed asset returns and unconstrained investors with Constant Absolute Risk Aversion (CARA) preferences. Such CARA-Normal framework has several limitations, which my co-authors and I relax by allowing for portfolio constraints ([1]), general distributions of asset payoffs ([3], [6], [7]), and general utility functions for investors ([6], [7]).

I summarize the distribution of my papers across research streams in Table 1. In the next section, I elaborate on my papers' contribution to each stream. Some papers span multiple streams; as a result, their total contributions are spread out across the corresponding sections.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Wealth effects and market quality	✓					✓	✓
Amplification of shocks and financial fragility	✓			✓			
Decentralized markets		✓			✓		
Generalizing CARA-Normal framework	✓		✓			✓	✓

Table 1: My research organized by stream. Rows are research streams; columns are papers.

A Wealth effects and market quality

Investors' wealth (or amount of assets under management, for institutional investors) can affect the way they trade by affecting (a) their willingness to bear risk, and (b) the tightness of their portfolio constraints. Traditional frameworks for analyzing liquidity and information efficiency assume unconstrained traders with CARA preferences, rendering them unable to speak to these wealth effects. In [1], [6], and [7] we develop models overcoming this shortcoming. Below, I will discuss the effects of wealth on liquidity and information efficiency, as highlighted by these papers.

A.1 Wealth effects and information efficiency

In [1], we study the interaction between information efficiency and funding constraints. We show that wealth effects can arise even with CARA utility when traders are subject to margin constraints. Such constraints arise when traders rely on financiers to fund their trades. For example, to build a long position, a trader can borrow from a financier, but he has to pledge a cash margin as collateral to cover potential losses. The trader can similarly establish a short position. With less wealth (i.e., with less cash or liquid, cash-like securities), a trader has less collateral and can only establish smaller positions. Thus, a lower wealth of traders is associated with tighter constraints. When constraints become tighter, traders must take smaller positions and thus profit less from their private information. Anticipating the reduced scope for profit, they acquire less information ex-ante. As traders acquire less information, the price becomes less informative about asset fundamentals in equilibrium. Thus, there is a negative association between traders' wealth and information efficiency. In [1], we also show that the interaction goes in the other direction: information efficiency affects the tightness of the constraints via its effect on the size of margins. This two-way interaction creates an amplification mechanism that I discuss in Section B.1.

The negative association between traders' wealth and information efficiency should continue to hold when the risk tolerance channel is at play. This is because (1) higher wealth translates into higher (absolute) risk tolerance (assuming a realistic case of decreasing absolute risk aversion (DARA) preferences), (2) higher risk tolerance implies more aggressive trading on private information, and (3) with more aggressive trading, more information is impounded into prices and so the information efficiency increases. In [6], we confirm this intuition. Moreover, our setup in [6] allows for heterogeneous wealth, thereby allowing us to examine not only the implications of changes in *average* wealth but also the implications of changes in *wealth distribution across traders* for information efficiency.

One of our key results in [6] is that transferring wealth from sufficiently wealthy to sufficiently poor traders increases information efficiency.[4] Put differently, wealth inequality is associated with lower information efficiency. This holds true even if the information is endogenous (and so wealthier traders are more informed). The intuition is best conveyed by noting that prices reflect the weighted average signal of all traders, with traders' weights proportional to their trading intensities. In the absence of wealth effects, a population of homogeneous traders (same risk aversion, same signal precision) would generate a price that conveys information through an equally weighted average of trader signals—a weighting scheme that also generates the most accurate possible posteriors for all traders. With wealth effects, however, trading intensities increase in wealth. As a result, the price no longer conveys an equally weighted average of signals, even if all traders have identical risk aversions and signal precisions. Instead, the price function emphasizes the signals of richer traders more than those of poorer traders, for reasons unrelated to signal accuracy, effectively creating an economy of "wealth-based discrimination for signals." In terms of price efficiency, this discrimination does not benefit anyone. Quite the opposite, by emphasizing the information of richer traders more, wealth inequality distorts the information content of prices away from the purely precision-based weights, thereby lowering price informativeness.

The implication is that policies aiming at reducing wealth inequality should contribute to better information efficiency. However, such policies might harm liquidity, as I explain in Section A.2. Here, wealth inequality should be understood broadly as both inequality in wealth of individual investors and concentration of assets under management among institutional investors.

A.2 Wealth effects and liquidity

The negative association between wealth inequality and information efficiency that we highlight in [6] (see Section A.1) also has implications for liquidity. The willingness of traders to provide liquidity (i.e., to accommodate increases in price by reducing their demand) is affected by information efficiency. Indeed, suppose that demand pressure from some traders leads to an increase in the price. If prices are informative, a trader of interest might not be willing to accommodate this price increase by reducing his demand. Such a price increase could be due to improved fundamentals, in which case selling the asset might not be profitable. Put differently, higher information efficiency exacerbates the adverse selection problem faced by traders and makes them less willing to provide liquidity. We confirm this intuition in [6]: We show that wealth inequality is associated with lower information efficiency and, via lower informativeness, with higher liquidity.

[4] Interpreting traders in the model as institutional investors (funds), our result will be: Transferring wealth (assets under management) from sufficiently large to sufficiently small funds increases information efficiency.

Thus, wealth inequality is a double-edged sword, contributing to improvements in market liquidity, but hurting information efficiency.

In [7], we consider a setup without asymmetric information, where the main determinant of liquidity is inventory risk. However, unlike in [6], where we consider a single-asset model, in [7], we allow for multiple assets. Our main measure of liquidity is (cross-)price impact, measuring how trading in asset i affects the price of asset j. We derive several results about the properties of price impact that arise only with wealth effects: (a) assets with independent payoffs can have non-zero cross-price impacts; (b) risk-free assets can be illiquid and can have non-zero cross-price impacts; (c) cross-price impacts can be asymmetric across assets; and (d) price impacts can be negative.

The key to these effects is that trading in an asset i exhausts wealth that can be deployed for trading other assets. Then, naturally, a change in the price of an asset where traders invest a bigger fraction of their wealth in equilibrium has a higher effect on their wealth. These assets will then have larger cross-asset price impacts. Similarly, in a situation of cash shortage, liquidity providers may need to sell existing assets to finance future consumption. In such a situation, following a selling pressure depressing the price of these assets, liquidity providers might need to sell more to still be able to finance their future consumption needs. The price impact in a situation of liquidity shortage can then be negative. In [7], we further discuss how these findings relate to recent episodes of illiquidity in risk-free assets in the UK and in the US, and how asymmetry in cross-asset price impacts could lead to the emergence of "systemic assets", i.e., assets whose sell-off triggers large moves in all security prices.

B Amplification of shocks and financial fragility

The interaction of several imperfections sometimes generates strategic complementarities, i.e., a situation where the actions of different market participants reinforce each other. Complementarities, in turn, are associated with the amplification of shocks and fragility, i.e., a situation where a small shock disproportionately affects a market. Below, I review two such mechanisms. The first is based on the interaction of financial constraints with asymmetric information, as in [1]. The second one is based on the interaction of market power with asymmetric information, as in [4].

B.1 Amplification via the interaction of financial constraints with asymmetric information

Funding constraints affect and are affected by informational efficiency. First, investors' incentives to acquire information and their capacity to trade on it are crucially affected by their ability to fund their trades. Thus, funding constraints should affect information efficiency. Second, since the information in prices can be useful for financiers to assess the risk of financing a trade, price informativeness should affect the tightness of funding constraints. In [1], we consider such a two-sided interaction between funding constraints and information efficiency in an REE model that allows for general portfolio constraints (see Section D.1 for a description of the model).

First, we show that constraints harm information efficiency: Tighter constraints mean that traders cannot speculate as much on their information and, hence, acquire less of it.[5] To study the effects of information efficiency on constraints, we assume investors finance their positions through collateralized borrowing from financiers who require the margins to control their value-at-risk(VaR). Such formulation is motivated by real-world margin constraints (see Brunnermeier and Pedersen (2009)). We argue that lower informational efficiency leads to tighter margins. The intuition is that, when prices are less informative, the price tracks fundamentals less closely, and financiers face more uncertainty about fundamentals and thus set higher margins.

In light of this, both margins and asset prices are determined jointly in equilibrium, leading to a novel *information spiral* shown in Figure 1 (left panel). Tighter funding constraints reduce the information acquired by investors, which reduces informational efficiency; reduced informational efficiency, in turn, leads to higher margins, which tightens investors' constraints.

One of the key implications of the information spiral is that a negative shock to investors' wealth is amplified and causes larger changes in asset prices than in a model with fixed signal quality and/or fixed margin requirements. A drop in investor' wealth tightens their constraints and leads to a drop in price informativeness. The effect of the wealth drop is reinforced via the information spiral. As a result, when investor' wealth is low, which we interpret as a crisis period, uncertainty is heightened, causing risk premium, return volatility, and the Sharpe ratio to rise. These results match empirical observations made during crisis periods such as the 2007–2009 global financial crisis.

Our mechanism provides a new crisis narrative and highlights an important role of specialist investors such as hedge funds—namely in enhancing price informativeness. Consistent with empirical evidence for equities (Barrot, Kaniel, and Sraer (2016)), in our model, as a crisis deepens, specialist investors face tighter portfolio constraints and become less capable of holding risky assets; meanwhile, nonspecialists like commercial banks and retail investors step up to provide liquidity. Nonetheless, risk premia, volatility, and the Sharpe ratio are elevated. We claim that this is because specialist investors are instrumental in making prices informative, and tightened constraints hinder them from

[5] I discuss this effect in more detail in Section A.1.

doing so. In short, complementary to existing intermediary-based crisis narratives in which nonspecialist investors are restricted from participating in the asset market, our mechanism shows how intermediaries matter even in markets where all investors can freely participate.[6]

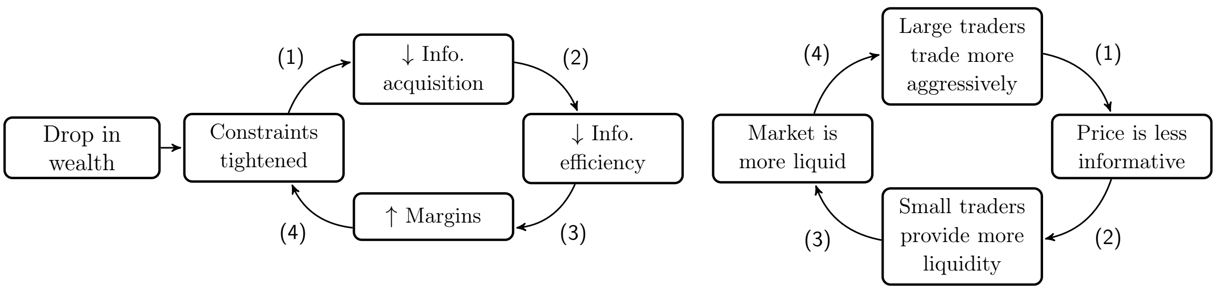


Figure 1: Amplification mechanisms in [1] (left) and [4] (right).

B.2 Amplification via the interaction of market power with asymmetric information, when large traders create noise

Large investors play an increasingly important role in asset markets in the U.S. and around the world. How does their presence affect liquidity and information efficiency? We address this question in [4]. We focus on two characteristics of large investors. First, due to their size, large investors have market power and their trades have a price impact. Second, they often trade for reasons unrelated to discount rates or cash flows, that is, the fundamentals. In doing so, they cause fluctuations in prices unrelated to fundamentals, or, add noise in prices. A salient example is institutional investors who put increasingly more weight on the environmental, social, and governance (ESG) performance of firms in their investment decisions.[7]

The key mechanism uncovered in this paper is a trading complementarity between large and other investors ("small" investors, hereafter) when large investors create noise. It is depicted in Figure 1 (right panel). When large investors trade more aggressively, prices reflect more of their own valuation which increases the amount of noise for small investors. Knowing this, small investors are less concerned with adverse selection (vis-à-vis other small investors) and are more willing to provide liquidity. The improved liquidity in turn encourages large investors to trade more aggressively. Importantly, this trading

[6]Restricted participation is a central assumption in intermediary asset-pricing models, in which intermediaries are typically the only agents who can hold risky assets. During crisis periods, the risk premia of these assets rises sharply, or prices drop substantially because otherwise, the constrained intermediaries would not be able to hold the entire supply of these assets. See He and Krishnamurthy (2018) for a survey on this literature.

[7]Thus, stocks that are likely owned more by ESG-conscious investors would thus have less informative stock prices. In [4], we find such a correlation in our empirical analysis using firm-level data.

complementarity does not arise when large investors do not exercise their market power and take prices as given.

This trading complementarity underpins three novel insights on the consequences of market power. The first concerns the effects of competition on market quality and investor welfare. Consider an increase in competition among large investors caused by a breakup of existing ones. Increased competition among large investors can *reduce* aggregate welfare and even make small investors worse off. As discussed above, more competition among large investors leads them to impound more noise into prices, thus making prices less informative and small investors' asset allocations less efficient, potentially translating into lower welfare. The unconventional result that competition harms welfare arises when informational friction is severe, by which we mean small investors have imprecise private signals and thus rely heavily on the price for inferences. If, instead, informational friction is low, aggregate welfare increases with competition. Our result suggests that competition policy in financial markets should take informational friction into account.

The second result shows that an improvement in the quality of private information can *reduce* informational efficiency. This seemingly paradoxical result stems from the aforementioned trading complementarity: Small investors endowed with more precise signals are less concerned with adverse selection and are more willing to provide liquidity. Higher liquidity, in turn, induces large investors to trade more aggressively, thereby injecting more noise into the price. This additional noise can dominate the effect of improved private information, resulting in a net decrease in informational efficiency. This unconventional result occurs when the informational friction is severe enough and the uncertainty about asset fundamental and large investors' private value is large enough. Again, when the informational friction is low, the conventional result prevails and better private information enhances informational efficiency.

The third result concerns the effect of market power on the stability of financial markets. The trading complementarity engenders an amplification mechanism whereby small shocks are magnified to have a disproportionate impact on market outcomes. Furthermore, multiple equilibria can emerge. These results do not arise when large investors take prices as given, suggesting that market power, in combination with informational friction, can be a source of fragility in financial markets.

C Decentralized markets

In traditional OTC market models, trade terms are set *bilaterally* between dealers and customers, while centralized markets rely on *all-to-all* trading in a single marketplace. Real-life markets often deviate from these models, neither being strictly bilateral nor all-to-all. My research on decentralized markets addresses these "intermediate" market types. For example, in markets such as corporate bonds, electronic platforms facilitate *one-to-many* matching, enabling customers to simultaneously seek quotes from many dealers. This aspect is examined in [2], where we assess the impact of these platforms. Similarly, markets like foreign exchange have a *two-tiered* structure that integrates centralized and OTC components. In [5], our focus is on analyzing the foreign exchange market's OTC (dealer-to-customer) and centralized (dealer-to-dealer) segments, from both a theoretical and empirical perspective.

C.1 Electronic trading platforms in OTC markets

In recent years, there has been a rise in electronic trading in OTC markets, mainly in the form of Request-for-Quote (RFQ). In such marketplaces, where many corporate bonds and derivatives are traded, a customer contacts multiple dealers for quotes and then trades with the one offering the best price. In contrast, the traditional models of OTC markets follow the pioneering work of Duffie, Gârleanu, and Pedersen (2005) and assume gains from trade are realized and split via *bilateral bargaining* (BB): Investors search for counterparties and are randomly matched over time. Upon successful matching, a buyer and a seller engage in Nash bargaining and split the trading gain according to their endowed bargaining power. In [2], we develop a theoretical model, tailored to the one-to-many matching between investors offered by electronic platforms. Specifically, a customer is allowed to query *multiple* dealers *at the same time*, hence the name "Simultaneous Multilateral Search" (SMS).

Our model follows Hugonnier, Lester, and Weill (2020), where a continuum of customers trade an asset through a continuum of homogeneous dealers.[8] All agents can hold either zero or one unit of the asset. The customers are subject to stochastic valuation shocks. Those who hold the asset but have a low valuation want to sell, while those without the asset but with a high valuation want to buy. They actively search for dealers according to independent Poisson processes with intensity ρ. We generalize the search process as follows to model SMS: (i) each searching customer can request quotes from up to n dealers; (ii) the best quote is determined via a first-price auction and (iii) the customer can potentially improve upon the best quote via bargaining: with probability q, the customer can make a take-it-or-leave-it offer (TIOLIO) to the winning dealer after the auction. Notably, the search process nests BB as a special case when $n = 1$: The searching customer randomly contacts one dealer and sets the price with probability q. With probability $1 - q$, the dealer sets the price. In that special case the parameter q thus serves as the customer's Nash bargaining power parameter, as in Duffie et al. (2005)

[8]In Hugonnier et al. the dealers are heterogeneous. We abstract from dealer heterogeneity to focus on SMS in a parsimonious way.

and Hugonnier et al. (2020).

Our model yields three novel insights. First, the two search parameters, the intensity ρ (how frequently one can search) and the capacity n (how many potential dealers one can reach), have contrasting implications for various equilibrium objects. For instance, a higher ρ always improves welfare. In contrast, a larger n can *hurt welfare.* The key mechanism is a "dealer bottleneck," arising from the asymmetric effects of n on the matching of the two sides of the market. To see this, suppose the asset is in excess supply and 90% of the dealers have inventory while the other 10% do not. Let us examine what happens when the capacity increases from $n = 2$ to $n = 3$: For a customer-seller, the matching rate with a no-inventory dealer increases from $1-0.9^2 = 19\%$ to $1-0.9^3 = 27.1\%$. Such an improvement in matching significantly adds to the asset inflow to dealers from customer-sellers. However, the outflow rate—the matching between customer-buyers and dealer-sellers—only increases by 0.9%, from $1 - 0.1^2 = 99\%$ to $1 - 0.1^3 = 99.9\%$. The negligible increase of the outflow rate is not at all enough to balance the significant rise in the inflow rate. That is, the asset is "clogged" at the dealers, creating a bottleneck that leaves more customer-buyers unmatched.[9] This leads to a surge in unrealized trading gains and may reduce welfare. To emphasize, this bottleneck effect is unique to the search capacity n. In contrast, the search intensity ρ does not create asymmetry in matching and always improves welfare.

Second, SMS allows to endogenize bargaining powers of customers and dealers. The key is the dual role of "dealer demographics"—how many dealers have the asset in their inventories and how many do not: As is standard, dealer demographics affect matching (e.g., how likely a customer can find a counterparty to trade). New in this model, dealer demographics also affect the split of trading gains between customers and dealers. For example, if there are many dealers able to accommodate a buy order, when contacted by a customer-buyer, they will quote more competitively, as they know that the customer has also contacted $n - 1$ other dealers, who very likely might also have inventories to sell. Such fiercer competition cuts more trading gains to the searching customer and less to the dealers. Thus, SMS endogenizes the bargaining powers, which are, by and large, exogenous in existing search models.

Third, our model reveals that customers do not necessarily prefer SMS to BB. We show that this choice ultimately boils down to the comparison between the two technologies' expected trading gain intensities, which are the respective products of (i) the search intensity—how frequently one can search, (ii) the matching rate—how likely it is to find at

[9] It is the increase of the unmatched customer-buyers that eventually balances the asset inflow to and the outflow from dealers in the steady state equilibrium. Whereas the inflow increases with n via the higher matching *rate*, the outflow increases via the increment in the larger customer-buyer population *size*.

least one counterparty, and (iii) the expected trading gain share—how much trading gain one can get given a match. The key is a potential downside of SMS for the customer's expected trading gain, which is determined by the endogenous competition among the contacted dealers. When such competition is insufficient, the customer expects the whole surplus to be captured by dealers, because any matched counterparty dealer will charge a monopoly price knowing that she is likely the only counterparty able to accommodate the customer's order (out of the n). In contrast, in BB, a customer always has some chance to secure some positive trading gains, given a positive bargaining power in BB.

C.2 Two-tiered markets

A growing literature in macroeconomics and finance emphasizes the role of dealers in price formation in the foreign exchange (FX) market. The previous literature focused on the interdealer segment of the FX market and abstracted away its two-tiered structure, characterized by two principal segments: the dealer-to-customer (D2C) and the dealer-to-dealer (D2D) segments. Such focus on the D2D market is likely due to a lack of data availability: While high-quality D2D data has been available for a while, the D2C data has not yet been publicly available. In [5], we leverage our access to unique proprietary data on the cross-section of D2C quotes, and study the joint price formation in the D2D and D2C segments of the FX market, both theoretically and empirically.

We develop a pure inventory model that accounts for the key prominent features of the FX market: two-tiered market structure, dealer heterogeneity, dealer market power in both D2D and D2C market segments, and non-exclusive customer-dealer relationship.[10] Analyzing such a rich model is a challenge, which we overcome by studying the model in the limit when dealer heterogeneity is small and focusing on the first-order effects of dealer heterogeneity.[11] This approach allows us to reduce the cross-section of D2C quotes to just a few summary statistics, facilitating both theoretical and empirical analyses. We believe it can be useful in other heterogeneous-agent settings as well.

Our theory establishes, and our empirical analysis estimates the following predictive relations between prices and bid-ask spreads in the D2D and D2C segments:

$$\begin{aligned} \text{Price}_{t+\ell}^{D2D} &= \beta_1^p E[\text{prices}_t^{D2C}] - \beta_2^p \operatorname{Cov}(\text{prices}_t^{D2C},\ \text{spreads}_t^{D2C}) + \text{const} + \epsilon, \\ \text{Spread}_{t+\ell}^{D2D} &= \beta_1^{BA} E[\text{spreads}_t^{D2C}] - \beta_2^{BA} \text{Var}[\ \text{spreads}_t^{D2C}] + \text{const} + \epsilon. \end{aligned} \tag{1}$$

Here, the lag value ℓ is 10 sec in our baseline specification; the variables on the right-hand

[10]Non-exclusivity means that customers direct their orders to dealers offering the best prices instead of directing them to a preferred, exclusive dealer.

[11]That is, we expand the equilibrium as the equilibrium in the homogeneous case, plus the corrections due to heterogeneity. We focus on the corrections that are first-order in the degree of heterogeneity.

side are summary statistics of the cross-section of D2C quotes at time t: $E[\cdot]$, $\mathrm{Cov}(\cdot,\cdot)$ and $\mathrm{Var}[\cdot]$ stand for, respectively, cross-sectional mean, covariance, and variance; prices refer to mid-prices and spreads refer to bid-ask spreads; in our theoretical analysis ϵ represent the higher-order effects in the degree of dealer heterogeneity, while in our empirical analysis it represents noise.

Our work yields several insights about FX market. First, it highlights dealer heterogeneity, exclusive customer-dealer relationship, and imperfect competition among dealers as FX market's important characteristics. Our theory predicts that all β's in (1) are positive. Our empirical analysis offers complete confirmation for these predictions. In contrast, if the D2D market was competitive or if dealers were homogenous, $\beta_2^p = 0$. With exclusive customer-dealer relationship, $\beta_2^p < 0$. Thus, the positive sign of β_2^p is the unique prediction of our theory, distinguishing it from other theories of two-tiered markets featuring no heterogeneity (e.g., Vogler (1997)), perfectly competitive D2D market (e.g., Dunne, Hau, and Moore (2015)) or exclusive customer-dealer relationship (e.g., Babus and Parlatore (2022)).

Second and third, our analysis reveals that the FX market is inelastic and non-competitive. Our theory relates the magnitudes of β's to the parameters of the model, such as dealers' risk aversion. Using the estimated values of β's, we calibrate the elasticity of the D2D market: A typical liquidity shock originating from the D2C market moves mid-prices in the D2D market by 0.5 basis points. This is comparable to the average bid-ask spread of 0.44 basis points. The D2D market is illiquid. Our estimates also imply that the D2D bid-ask spreads would have been 12.5% smaller if dealers had not exercised their market power. Thus, due to market power, the dealers charge an additional 12.5% markup for liquidity provision. Relatedly, the entry of an additional dealer increases elasticity by 9.45%. The D2D market is non-competitive. Combining our elasticity estimates with statistics on the arrival frequency of liquidity shocks and their distribution, we obtain that the liquidity shocks account for around a third of overall short-term volatility in the FX market. The inelastic market hypothesis (Gabaix and Koijen, 2021) holds for the FX market.

D Generalizing CARA-Normal framework

Imperfect competition and asymmetric information are salient features of modern financial markets. The theoretical literature on markets with either of the two frictions mostly relies on a CARA-Normal framework: traders have constant absolute risk aversion (CARA) utility functions, and asset payoffs are normally distributed.[12] Such a framework is very

[12] See Rostek and Yoon (2023) for a survey of the theory of imperfectly competitive financial markets. See Brunnermeier (2001) and Vayanos and Wang (2013) for a survey of the theory of asset markets under

tractable due to the linearity of equilibria that it produces. Understandably, it became a "workhorse" among financial economists, myself included. Nevertheless, it also has important limitations: (a) CARA utility implies the absence of wealth effects, meaning that the trading of investors is unaffected by their wealth; (b) normal distribution implies that higher moments play no role and that asset payoffs can become negative; and (c) within the framework, investors do not face trading constraints.[13] In a series of papers, my co-authors and I relax these limitations by allowing for portfolio constraints ([1]), general distributions of asset payoffs ([3], [6], [7]), and general utility functions for investors ([6], [7]). This allows us to expand the set of analytically tractable theoretical models, which helps to explain the empirical regularities and to tackle the economic tradeoffs that standard models cannot address.

D.1 Portfolio constriaints

In [1], we consider an asymmetric-information rational expectation equilibrium (REE) model with general, price-dependent portfolio constraints. We examine one of the basic tenets of financial economics, which states that market prices aggregate investors' information.

The core of the information aggregation argument is that investors acquire information about future asset values and trade on it, thereby impounding that information into price. This argument presupposes that investors have incentives to acquire information and the capacity to trade on it, where each of these factors is crucially affected by investors' ability to fund their trades. Thus, an important question arises: How do funding constraints faced by investors affect information efficiency? The main challenge in studying this question is that most noisy rational expectation equilibrium (REE) models, which are instrumental in analyzing informational efficiency cannot accommodate constraints in a tractable manner. In [1], we tackle this challenge and develop a tractable REE model with general portfolio constraints.

We consider a canonical CARA-normal REE model in which investors trade to profit from their private signals about the risky asset's fundamental value and to hedge their endowment shocks. The novelty is that we allow for general portfolio constraints: investors can only trade up to some maximal long and short positions of the risky asset, and these portfolio constraints can be any function of price. This general, price-dependent specification of portfolio constraints nests many types of real-world trading constraints,

asymmetric information.

[13] All three points are likely not true in reality: (a) wealthy and poor traders have different propensities to take risks; (b) higher moments (such as skewness) matter for asset prices, while negative payoffs are unrealistic due to limited liability and (c) trading constraints, such as short-sale or margin constraints are prevalent in most of the markets.

such as short-sale constraints, borrowing constraints, margin requirements, etc.

We then apply our methodology to study how portfolio constraints interact with informational efficiency. We show that this interaction gives rise to a novel information-based amplification mechanism, which we call the *information spiral.* I discuss this amplification mechanism in Section B. The dependence of tightness of constraints on investors' wealth gives rise to wealth effects, even with CARA utility. I discuss the implications of such wealth effects in Section A.

D.2 General distribution of asset payoffs

In [3], we consider a model of strategic liquidity provision with many assets and general distribution of asset payoffs. We investigate determinants of liquidity for assets with non-Gaussian payoffs in the presence of strategic trading.

Many modern financial markets are illiquid and in the sense of being unable to accommodate large trades without a price change.[14] Large traders and institutional investors, such as mutual and pension funds, respond to illiquidity by trading *strategically*, that is, accounting for their price impact. How are illiquidity and asset prices determined in equilibrium when investors internalize their price impact? As we discussed, the literature on strategic trading addresses this question by adopting a *CARA-normal* framework for tractability. The limitations of this framework make it inapplicable to derivative markets, where payoffs are nonlinear functions of the underlying asset prices and, hence, cannot be Normal. Notably, multiple derivatives written on the same asset must be studied jointly. Thus, to study illiquidity in derivative markets, we need a model of strategic trading for multiple assets with non-Gaussian payoffs. In [3], we develop such a model and test its predictions using the data on US stock options.

We assume that a finite number of CARA traders, whom we refer to as *liquidity providers* (LPs), exchange multiple risky assets for a riskless asset over one period while internalizing their price impact. LPs all have the same risk aversion and are symmetrically informed. The absence of information asymmetry implies that, in our setting, the unique source of price impact is inventory risk.[15] In addition to LPs, uninformed *liquidity demanders* (LDs) submit market orders. Trading is organized as a uniform-price double auction: traders simultaneously submit demand functions specifying the number of units of the assets they want to buy as a function of the prices of all assets. All trades are exe-

[14] For example, Koijen and Yogo 2019 estimate that, for the median U.S. risky asset, the price impact of a 10% demand shock was consistently greater than 20% between 1980 and 2017. The effects of illiquidity are even more severe for derivative contracts, where even short-term at-the-money (ATM) options written on the largest stocks can have bid-ask spreads on the order of 2%.

[15] Recent empirical results documenting that inventory risk is a dominant source of price impact in options markets justify our focus on inventory risk (Muravyev 2016).

cuted at prices that clear the market. Our main innovation (as compared with previous research) is to allow for an arbitrary distribution of the risky asset payoffs.

Despite significant technical challenges, we characterize equilibrium explicitly and are able to derive its properties analytically: We show that solving for equilibrium reduces to solving an Ordinary Differential Equation (ODE), which is linear and, thus, can be solved in closed form. In an application of our theory, we derive several surprising implications regarding option bid-ask spreads: Option bid-ask spreads may decrease in risk aversion, physical variance, and open interest, but they may increase after earnings announcements.[16] All these predictions are confirmed empirically using a large panel data set of U.S. stock options.

In [7], we further generalize [3] to allow for general preferences. Thus, [7] features strategic trading, general distribution of asset payoffs, and general preferences, but no asymmetric information. In [6], we allow for asymmetric information, general distribution of asset payoffs, and general preferences, but consider a large economy with price-taking investors. Given that the main implications in [6] and [7] stem from the generality of preferences, I discuss these papers in Section D.3.

D.3 General utility functions

Wealth effects and market quality in a large economy

In [6], we introduce an asymmetric-information asset-pricing framework featuring general utilities and general asset payoff distributions. We investigate how changes in wealth distribution affect different aspects of market quality (information efficiency, liquidity, and trading volume).

Investors' wealth (or the amount of assets under management for institutional investors) affects their willingness to take risks and should matter for how willing they are to provide liquidity and to speculate on their private information. How do these effects aggregate? Which characteristics of wealth distribution matter for liquidity and information efficiency? The existing literature does not provide a definitive answer to these questions, perhaps because the standard framework for analyzing liquidity and information efficiency assumes CARA preferences that do not feature wealth effects.[17] To study the effects of wealth distribution on liquidity and information efficiency, we need a model that features non-CARA preferences (to have wealth effects), investor heterogeneity (to

[16] Our model has the same surprising implications for price impacts. In the paper, we focus on bid-ask spreads because it is the illiquidity measure we work with in our empirical exercise.

[17] A notable exception is Peress (2004). Our answers about the effects of wealth on information efficiency are different from and complement those in Peress (2004). The model in Peress (2004) does not speak to the effects of wealth on liquidity.

be able to accommodate non-degenerate wealth distributions), and asymmetric information (to be able to speak to information efficiency). In [6], we develop such a model and examine the effects of changes in wealth distribution on different aspects of market quality.

We introduce a tractable framework with heterogeneous traders and general preferences. Our setup begins with a large economy modeled as a continuum of traders indexed by $a \in [0, 1]$, with trader characteristics (risk aversion, signal precision, and so on) represented as arbitrary continuous functions of a. Our baseline case of log-normally distributed payoffs is particularly transparent and offers a log-linear equilibrium where all quantities are in closed form.[18]

This kind of tractability is rarely seen in models with fully heterogeneous agents and/or non-CARA utilities. What enables it in ours is the way we model information. In contrast to the traditional methodology for large markets (Hellwig, 1980, and subsequent literature) we do not assume that traders have signals of finite precision because that would imply that as the number of traders becomes large, so does the total amount of information.[19] What is more, with signals of finite precision, traders make finite speculative trades, with the unfortunate consequence that aggregate demand would explode for large numbers of traders.

We instead use an assumption similar to Section 9 in Kyle (1989), whereby the total finite amount of information is distributed among all traders. By definition, then, the total amount of information is always finite, irrespective of the number of traders. In addition, as traders base their demands on signals with precision inversely related to the size of the economy, aggregate demand remains finite even when the number of traders becomes infinite.

A key contribution of our paper is to extend the above information structure from Kyle (1989), turning it into a general formalism for economies with continuums of small heterogeneous signals. As it turns out, the right formalism uses a type of stochastic calculus, where the dimension that typically represents time is "transposed" to represent traders.[20]

To fix ideas, we offer the following example. Suppose we represent a continuum of agents as a unit interval. Using a to denote one of the agents, let us imagine that a

[18] Our framework is still tractable with general probability distributions.

[19] As the total amount of information is the precision of the sufficient statistic of private signals, it equals the sum of signal precisions held by all traders. Thus, in economies where the precision of each signal is finite (as in "neither infinite nor infinitesimal," i.e., neither infinitely large nor infinitely small), the total amount of information grows directly in the number of traders.

[20] See Gârleanu, Panageas, and Yu (2015) for a similar trick applied to firms rather than traders.

lives on a segment of size da and that he observes the signal

$$ds(a) = v\,da + dB(a), \tag{2}$$

where v is the fundamental value of a traded asset, and where $dB(a)$ is an increment of a Brownian Motion. The aggregate sum of all signals—a sufficient statistic for all private signals—is an Itô integral, a key property that gives us access to the full arsenal of stochastic calculus. But perhaps even more importantly, this type of aggregation also allows us to think of the noise component of the sufficient statistic as consisting of a large number of small idiosyncratic shocks, resembling what Black (1986) calls "noise in the sense of a large number of small events."

Using the tractability offered by our model, we then study how changes in wealth distribution affect information efficiency, liquidity, and trading volume. I discuss these implications in Section A.

Wealth effects and liquidity in an economy with large investors

In [7], we consider a model of strategic liquidity provision with many assets, general distribution of asset payoffs, and general utilities. We contrast the theoretical properties of the market liquidity in a model with CARA traders to that in our general model featuring wealth effects.

Large institutional investors dominate modern markets. After the Global Financial Crisis, many of these investors have been classified as systemically important financial institutions (SiFi): Institutions whose collapse would pose a serious risk to the global economy. One of the key channels through which SiFis may impact financial markets is through their portfolio liquidation decisions: When hit by a shock, large institutions may need to simultaneously adjust their portfolio holdings, which may lead to large adverse movements in market prices due to the SiFi's market impact and/or their inability to provide (enough) liquidity. While formerly viewed as an artifact of risky, informationally sensitive securities, recent turmoils in the government bond markets show that illiquidity is a major consideration even for extremely liquid, money-like securities.[21] In equilibrium, this illiquidity should be priced: The most illiquid securities should trade at a discount, while liquid securities should trade at a so-called "flight-to-liquidity" premium. In order to understand these effects, we need a theoretical model of liquidity determination in a

[21]For example, in October 2022, funding liquidity frictions of British Pension funds (large, strategic investors in British government bonds) triggered a serious turmoil in the bond market, forcing the central bank to intervene. See, e.g., Pinter (2023). Even the market for US Treasury bills, commonly viewed as "money-like" and extremely liquid, is impacted by large money market funds whose strategic behavior affects T-bill rates. See, e.g., Doerr, Eren, and Malamud (2023).

market populated by large (in terms of wealth or amount of assets under management) investors who internalize their price impact. The goal of [7] is to develop such a model.

Our model generalizes that in [3] (see Section D.2 for a description) by allowing for general preferences. We show that solving for equilibrium reduces to solving a non-linear ODE. Generally speaking, this ODE does not admit closed-form solutions. Nevertheless, we are still able to obtain analytical results.[22] We show that the price impact in our general model may differ significantly from that in a CARA model (like the one in [3]): (a) assets with statistically independent payoffs can have non-zero cross-price impacts; (b) risk-free assets can be illiquid and can have non-zero cross-price impacts; (c) cross-price impacts can be asymmetric across assets; and (d) price impacts can be negative. I discuss these effects in Section A.2.

[22]We use comparison theorems for ODEs to derive comparative statics and also derive asymptotic results when preferences are close to CARA and when the number of investors is large.

E Future research

Paper [6] offers a way to analyze several market imperfections within a single tractable framework. It is *portable*, meaning that it can be embedded into other models, and it is *flexible*, meaning that it can easily be extended to allow for other features, such as dynamics, multiple assets, and market power. These two features help [6] set an agenda for my future work.

E.1 Endogenizing the wealth distribution

What determines the distribution of wealth across investors? Existing literature is silent on information as one of the determining factors. Yet it should be an important one: private information of better quality enables investors to earn higher trading profits, translating into higher future wealth. Our framework in [6] offers a way to combine wealth effects with asymmetric information, making it possible to analyze how private information contributes to wealth inequality or determines the cross-sectional distribution of wealth. Yet, in [6], the wealth distribution is exogenous.

There are several ways to endogenize the wealth distribution. In ongoing work, Efstathios Avdis and I endogenize the wealth distribution by requiring it to be "trade-invariant," i.e., such that the distribution of wealth across traders does not change as they trade.[23] This way, we obtain two distinct equilibrium objects: in addition to the informational efficiency we typically see in the literature (a scalar), we must now obtain the distribution of wealth (a function). Our analysis shows that our framework offers a tractable way of analyzing this distribution, by reducing the problem to solving the Kolmogorov Forward Equation (KFE), a stochastic calculus tool familiar from continuous time models. Our preliminary analysis also demonstrates that, under certain conditions, the trade-invariant distribution of wealth distribution obeys a power law.[24]

Another way to endogenize wealth distribution is to consider its long-run distribution in a dynamic model. I discuss a potential dynamic extension of [6] in Section E.4.

[23] This is indeed possible, even though the wealth of each individual trader *does* change. All we need is that, as agents trade, their new wealth values, viewed as a random variable, are drawn from the same distribution as their old wealth values.

[24] These results were part of an earlier version of [6]. We are working on expanding these results and including them in a separate paper.

E.2 Interaction of market power, heterogeneous information, and wealth effects

In [6], we consider a large economy with price-taking investors. Yet, despite the infinite number of traders, the market in [6] is not infinitely liquid. Thus, each trader has a non-zero price impact in equilibrium. How would the equilibrium change when traders account for price impact? It might be tempting to conclude that the equilibrium wouldn't change since it would be paradoxical to have small traders having a non-negligible price impact in equilibrium. Yet the equilibrium changes, as we show in our paper with Efstathios Avdis extending [6] to allow for *market power*. The resolution of the paradox is as follows. Each of the small traders submits an infinitesimal demand *in equilibirum*. The impact of their *equilibrium demand* on the price is then small. Yet, had they chosen to deviate and submit a finite demand, they would have moved the price by a finite amount. Their *marginal* impact on the price is then non-zero. It is the marginal effect that matters. As a result, the large-economy limiting equilibrium in the economy where traders account for their price impact differs from that in the price-taking economy.[25]

Our extension of [6] with market power is tractable: in our ongoing work, we already established equilibrium characterization and analyzed its main properties. Our framework can be used to investigate the interaction between market power, heterogeneous information, and wealth effects in a parsimonious setup. Preliminary analysis shows that, compared to the model in [6], the model with market power: (i) can exhibit strategic complementarities resulting in multiple equilibria and fragility and (ii) can feature a different trade-invariant wealth distribution, underscoring the importance of market power in determining such distribution.

E.3 Information economics in limit order markets

Many centralized markets, such as equities, are structured as limit order books. These markets operate via limit orders, which are instructions to buy or sell a specific quantity of an asset at a specific price or better. A buy (resp., sell) limit order can only be executed at the limit price or lower (resp., limit price or higher). There is also the execution priority of the limit sell (resp. buy) orders placed at lower (resp. higher) prices.

The common metaphor of centralized markets is a uniform price auction (UPA), where traders submit demand schedules, and all trades are executed at the price that

[25]Here is another explanation. Without accounting for price impact, the traders $a \in [0,1]$ submit small demands dx_a that aggregate to $\int_0^1 dx_a$. With price impact, they scale down their demand and submit $k_a dx_a$, where k_a is a factor less than 1. Each of these demands is still small and still has a negligible impact on the price (*in equilibrium*), yet the aggregate demand $\int_0^1 k_a dx_a$ differs from $\int_0^1 dx_a$, implying the difference in all aggregate equilibrium quantities.

clears the market. Demand schedules are interpreted as a collection of limit orders. A point on a demand schedule $x(p) > 0$ represents a limit order to buy quantity x at a price p or lower. In UPA, only one limit order, corresponding to the market clearing price p^*, is executed. This contradicts the execution priority: the limit orders in a downward-sloping schedule $x(p)$ for quantities smaller than $x(p^*)$ are offered at better prices and must be executed.

Thus, a better approximation to a limit-order market is a discriminatory price auction (DPA), where traders' limit orders at prices up to the market-clearing price are executed at limit prices, not the market-clearing price. Do the main results in information economics hold true when we assume a DPA market structure instead of UPA? We investigate this question in an ongoing work with Efstathios Avdis.

Existing auction theory cannot accommodate heterogeneous information in DPA in a tractable manner. The reason is technical: for the solution technique to work, it is important that the uncertainty faced by each bidder aggregates to a scalar sufficient statistic. This translates into the requirement of equilibrium demands being additively separable in private information. In UPA, such additive separability is guaranteed within the CARA-Normal setting. In DPA, even the CARA-Normal setup does not yield additive separability.

Our preliminary work shows that the CHILE (Continuous Heterogeneous Information Large Economy) limit (as in [6]) yields additive separability of demands, even in DPA. We can then obtain a tractable equilibrium in a DPA with heterogeneous information. We also see that some important information economics results could change when applied to limit order markets. The reason is that, in limit-order markets, the information is useful not only for predicting the fundamental value but also for predicting which of the limit orders will be executed. DPA always features ex-post regret. If a trader gets allocated q units of the asset, he regrets submitting limit orders for quantities $x < q$ with limit prices $I(x) > I(q)$ (assuming downward sloping demands). Private information helps to minimize this ex-post regret (in addition to learning about the fundamentals). In contrast, in UPA, demands are ex-post optimal, and so there is no ex-post regret.

E.4 Bridging asset pricing and market microstructure

Neoclassical asset pricing and market microstructure both study asset markets, yet they use very different models. Asset pricing models, such as those covered in Cochrane (2009), are typically dynamic and with agents having realistic preferences (e.g., Epstein-Zin). They typically can be calibrated successfully to match various moments of asset prices. Yet, these models are typically frictionless and do not speak to other characteristics, such as trading volume, information efficiency, and liquidity. These characteristics are the realm of market microstructure. Yet models there typically use simpler preferences (such as CARA) and are often static. Consequently, such models cannot be calibrated to match the asset pricing moments, even though they can successfully speak to market quality and trading volume. A goal of my ongoing work with Efstathios Avdis, Christoph Frei,[26] and Raphael Huwyler[27] is to develop a framework that would bridge these two literatures, allowing for dynamics, realistic preferences, and frictions, such as heterogeneous information and, perhaps, market power.

We aim to extend the CHILE model ([6]) to continuous time. In [6], we use Brownian motion to model noise in the cross-section of agents' signals. With time dimension, we need a stochastic process that evolves both in cross-section and over time. Such a 2-parameter Brownian motion is often referred to as Brownian field. While the mathematical theory of Brownian fields is more recent than that of a Brownian motion, it has already found its applications in finance, in modeling the dynamics of yield curves.[28] Our current setup in this project involves a dynamic, continuous time extension of [6] with noise modeled as a Brownian field.

To see how such an approach can be fruitful, note that the static model in [6] can be viewed as a perturbation of a neoclassical model (without private information) by introducing small private signals. Since the perturbation is small, the tractability of the unperturbed model is preserved. The idea is that, if we similarly perturb a dynamic model, such as that of Merton (1969), we should similarly retain the tractability of the original model, while generalizing it to asymmetric information. Alternatively, [6] can be viewed as a generalization of a microstructure model, allowing for more general preferences. The idea is that similar to the static setting, one could generalize in a similar way a dynamic model such as Wang (1993) or Kyle, Obizhaeva, and Wang (2018).

[26] Christoph Frei is a Professor of Mathematics at the University of Alberta.

[27] Raphael Huwyler is a PhD student in Mathematics at the University of Alberta.

[28] To model the dynamic of a yield curve, one needs shocks that differ across maturities and over time. Brownian field is one way to model such shocks; see Goldstein (2000) and Collin-Dufresne and Goldstein (2003).

III Teaching statement

I was born into a family of teachers.[29] From my parents, I've inherited the attitude that teaching is an important and rewarding job that requires effort and devotion. In this section, I describe my teaching at INSEAD. First, I summarize my teaching portfolio and effectiveness across programs. Next, I describe the pedagogical material I developed for each program separately.

A Teaching portfolio and effectiveness

As a junior faculty member, I adhere to the standard practice in the Finance Area of concentrating on teaching core MBA courses, which is considered both an efficient and less risky teaching arrangement. Consequently, most of my teaching load is concentrated in the MBA program, where I teach Corporate Financial Policy (CFP), the second core finance course. The aim of this course is to explore various elements of corporate finance policy within the context of an imperfect real-world environment. CFP nicely complements my research. Both study finance in an imperfect world. My research focuses on asset pricing, whereas the CFP course focuses on corporate finance. In the PhD program, I teach Continuous Time Finance, the core course on stochastic calculus and its applications to finance. There, I teach both the classic papers on continuous-time portfolio choice and general equilibrium and some more recent applications of stochastic calculus, such as those I use in my research ([6]).

I have adapted to INSEAD's demanding teaching environment relatively quickly, with an average teaching rating of 4.1 out of 5 in my first year, and 4.5 out of 5 for the past three years. I received the Dean's Commendation for Excellence in MBA Teaching in 2021. Section A in the Appendix provides more details on teaching loads and ratings for the various courses that I taught. I have also contributed to the teaching in the school by being a teaching mentor for Junyuan Zou and by developing new pedagogical material: new classes for both my PhD and MBA courses and a case and a simulation for the core MBA course.[30] I describe this new pedagogical material in the next section.

[29]My career represents a statistical anomaly in the family. My mother, father, sister, grandmother, uncle, aunt, and cousin are all high school teachers. Moreover, they all work (or used to work) in the same school. This is also the school all of us have graduated from.

[30]The case, "Square Inc's Valuation in 2014" is co-written with Lily Fang and John Kuong. The simulation "Trading Games and Arbitrage Pricing" is co-developed with Junyuan Zou.

B Pedagogical development

B.1 MBA teaching: Corporate Financial Policy (CFP).

CFP is the second core finance course in the MBA program. The course aims to understand the effects of various imperfections (such as information asymmetries and conflicts of interest) on different aspects of corporate financial policy (such as capital structure and payout policy). The first half of the course is devoted to derivatives. This part of the course is often challenging for the students, as they have to grasp rather complicated technical material in a short period of time. To help students with this challenge, my colleagues and I have developed several new pedagogical materials. The first one is a simulation that introduces the students to derivatives trading and pricing in a fun, gamified way. The second one is a case that shows the applications of derivatives pricing in venture capital, which is the field students are very excited about.

Simulation: "Trading Games and Arbitrage Pricing." In this simulation developed with Junyuan Zou, the students are trading forward contracts in a trading game environment that is close to that in the real financial markets. The goals of the simulation are twofold. First, the students are introduced to forward pricing and the concept of arbitrage in the gamified environment. Instead of being taught about arbitrage strategies and forward pricing, students discover such strategies and see how the pricing works during the game. We then study the related course material by debriefing the game. Such an approach makes studying the material more fun and engaging. Second, students see that the theory they study in class works: the forward price in the game is typically equal to the theoretical price derived in the class. I present the description of the simulation and the debrief of a typical outcome in Appendices B and C.

The simulation has proved to be an effective pedagogical tool, receiving positive feedback from students and improving the dynamics in class. Junyuan Zou, Alexandru Barbu, and I use the simulation for CFP teaching. Joel Peress uses it in EMFin and ARAMCO MFin Module 2 "Capital Markets II." Before 2024, we used the prototype version developed and programmed solely by Junuan and me. Having fine-tuned the prototype version, in fall 2023, we requested R&D funding to develop an "alpha" version for the simulation. This version is scheduled to roll out in January 2024.

Case: "Square Inc's Valuation in 2014." This case, co-written with Lily Fang and John Kuong centers on the intricate financial instrument known as convertible preferred shares, which were issued by Square Inc. in 2014. These shares are a popular choice for startup financing, and they feature complex, option-like characteristics. The study highlights the importance of these characteristics by i) analyzing how they affect the payoffs of shareholders and investors, ii) evaluating their significant economic impact, and iii) demonstrating the extent of Square Inc.'s valuation error when these features are not considered. I present the case and the set of teaching slides in Appendices D and E.

The case study is based on a recent academic paper by Gornall and Strebulaev (2020) that shows that ignoring the option-like features in convertible preferred shares leads to a systematic misvaluation of US startups. The case development exemplifies my teaching philosophy of bringing the latest academic research (not necessarily in my field) to the classroom. This case has been frequently utilized internally by myself, John Kuong, Lily Fang, Junyuan Zou, and Alexandru Barbu. The students in my CFP classes have consistently expressed high regard for the case's relevance and have valued the chance to implement their learning about option pricing from the course.

New session: IPOs. When the course was expanded from 12 to 14 sessions in 2017/18 as part of the MBA curriculum review, I added a new session on IPOs. In this session, we talk about the goals and the pros and cons of going public, cover the main IPO methods (underwritten IPO, direct listing, auction IPO), discuss some recent phenomena, such as the use of SPACs, and talk about some puzzles such as IPO underpricing. We also talk about the mechanics of the IPO process in a concrete example of some recent IPOs. Most recently, I used the IPO of SNAP Inc., the company behind Snapchat, as the leading example. This session features very recent topics and examples, which engages students, leading to good in-class dynamics and overall evaluation of the session. My slides for this session are in Appendix F.

New session: the case of Hertz. As part of the same course expansion, I added a new case on Hertz's 2006 IPO, backed by private equity sponsors. We cover this case in the last but one session of the course. It allows for discussion of various frictions, such as agency problems and asymmetries of information, and various aspects of corporate financial policy in the case context. Thus, it shows the practical applications of the issues studied in the course. It also allows us to discuss private equity and leveraged buyouts, the topics the students are excited to learn about.

Excel spreadsheet: from Binomial to Black-Scholes model. I developed a new Excel spreadsheet used in session 4 of CFP (The Black-Scholes Model). The spreadsheet visually demonstrates that the seemingly incomprehensible Black-Scholes model is a limit of a much simpler binomial tree model with many periods. Since we study the Binomial model in class in great detail, the Black-Scholes model is no longer a "black box" to students, and they get a much deeper understanding of it. The spreadsheet was used by Theo Vermaelen, John Kuong, Junyuan Zou, and Alexandru Barbu in their teaching of

CFP.

B.2 PhD teaching: Continuous Time Finance

This course is split into two parts. In part A (five three-hour sessions), we cover the foundations of stochastic calculus and its applications to portfolio choice and general equilibrium. I've inherited this course from Bernard Dumas, and for part A, I've only revised the slides to adapt to my teaching style: I typically leave "blanks" on my slides (parts of proofs, solutions to simple examples), which I fill during the session by annotating the slides. We discuss some more recent stochastic calculus applications in part B (five three-hour sessions). There, I've developed new sessions on continuous time dynamic contracting, continuous time macro models, dynamic information design, search models, and stochastic calculus applications to noisy rational expectations models (as in [6]).

IV Service statement

In this section, I summarize my contributions to the school, the area, and the PhD program.

A Service to School

One key aspect of my contributions to the school is enhancing external research visibility. Since joining INSEAD, I have delivered over 30 talks, including regular presentations at premier conferences in our field. These include the American Finance Association Meetings, the Western Finance Association Meetings, and the European Finance Association Meetings. Additionally, I've presented my research at various academic institutions, including in the top 10, and served as a discussant at multiple conferences. See my vita for the comprehensive list of my talks and discussions. I am a member of the Finance Theory Group (FTG) since 2022 and a research affiliate of the Center for Economic and Policy Research (CEPR) since January 2024. My work has been covered by Bloomberg and my involvement with INSEAD Knowledge has further helped in disseminating my work to a wider audience (see Section C). I have also served as an ad-hoc referee for over 40 papers submitted to journals in finance and economics and have been a program committee member at several conferences. This information is summarized in Section D.

B Service to Finance area

My involvement in the finance department includes playing a significant role in faculty recruitment. For recruiting new faculty, I consistently contributed by evaluating application files in both initial and secondary rounds, interviewing candidates at the AFA annual meetings, participating in job talk assessments, and providing thorough feedback to assist the department in decision-making.

Furthermore, I co-organized the weekly finance seminar and the internal brown bag seminar series. In the academic years 2018/19 and 2019/20, I collaborated with Bart Yueshen. We hosted about 30 renowned researchers each year to present at our finance seminars. These seminars also featured presentations by INSEAD colleagues and PhD students, fostering a dynamic and collaborative academic environment. I have also actively participated in the planning and organization of the INSEAD Finance Symposium in 2020, 2021, 2022, and 2023. This symposium, spanning 1.5 days, featured academic presentations and served as a platform for not only our own faculty to present and engage in scholarly discussions, but also for attracting academics from globally renowned institutions such as Duke University, Wharton, UCLA Anderson, London Business School, and HEC Paris.

C Service to PhD program

In addition to my teaching responsibilities, I have made other contributions to the PhD program. I was a part of the dissertation committee for Dmitry Chebotarev, who joined Indiana Kelley in 2022, and Dima Pugachev, who joined the Norwegian School of Economics in 2023. I currently serve as an advisor to Nikola Kiprijanovski.

Over the years, I have been actively engaged with PhD students, offering them regular feedback on their projects. For those preparing for the job market, I reviewed their job market papers, participated in their practice job talks, and conducted mock interviews to enhance their preparedness. Additionally, I have played a role in the admissions process of PhD students by reviewing their applications.

V Supplemental evidence: research

A Invited seminar talks, conference presentations and discussions

1. I have presented at 10 research seminars at universities around the world, including at universities among the top (see my vita).

2. My work has been presented at 35 conferences, including the very best in terms of visibility and quality, such as FTG meetings, American Finance Association meetings, Western Finance Association meetings, Society for Financial Studies Cavalcade Conference, Adam Smith Workshops, European Association meetings (see my vita).

3. I have given 14 discussions in academic conferences around the world (see my vita).

B Professional affiliations

I have been a Finance Theory Group (FTG) member since 2022.[31] Starting January 2024, I am also the Center for Economic and Policy Research (CEPR) research affiliate, Asset Pricing group.[32]

C Media coverage

My research had an impact beyond academia and raised (unsolicited) media attention. In particular, an earlier version of [4] received coverage from Bloomberg.[33] This unsolicited media coverage demonstrates the relevance of my research for the real world. In addition, I popularize my research by writing for INSEAD Knowledge.[34]

D Reviewing for Journals and Conferences. Membership of Dissertation Committees.

1. I regularly act as a referee for many finance and economics journals, including *American Economic Review (×1), Econometrica (×2), Review of Economic Studies (×1), Journal of Finance (×8), Review of Financial Studies (×9), Journal of Financial Economics (×1), Journal of Economic Theory (×5), AEJ: Micro (×1), Management Science (×7), Review of Asset Pricing Studies (×2), Journal of Financial*

[31] Finance Theory Group is a professional organization dedicated to advancing theoretical research in financial economics. Membership in this organization is competitive, and new members are elected by the vote of the board. No more than 12 members can be elected each year.

[32] CEPR is a pan-European economic think tank, built on the principles similar to that of the National Bureau of Economic Research (NBER) in the US. Membership in CEPR is competitive and by invitation only.

[33] See Bloomberg, 5 September 2017,"Lots of Liquidity Isn't Always Better."

[34] INSEAD Knowledge articles can be found at https://knowledge.insead.edu/author/sergei-glebkin.

and Quantitative Analysis (×2), Mathematics and Financial Economics (×1), and Journal of Economic Dynamics and Control (×3).

2. I have been a program committee member at several conferences: *European Economic Association meetings* (2023–present) and *Northern Finance Association meetings* (2017–present)

3. I have been an external examiner for Etienne Borocco's doctoral dissertation (Paris Dauphine PhD 2019, now in industry). I was a member of the dissertation committee of Dima Pugachev (INSEAD PhD 2023, placed at Norwegian School of Economics) and Dmitry Chebotarev (INSEAD PhD 2022, Placed at Indiana Kelley).

E Citations

My Google Scholar citation count is 64 as of December 2023. All of my papers were published very recently (three in 2023 and one in 2021). Thus, I expect this number to change significantly in the next several years. Assuming that the growth rate in my citations does not change in the next five years, my cumulative citation count will reach 1000 three to five years from now (beginning of 2024). The evolution of cumulative citation count and its log-linear fit are represented in Figure 2.

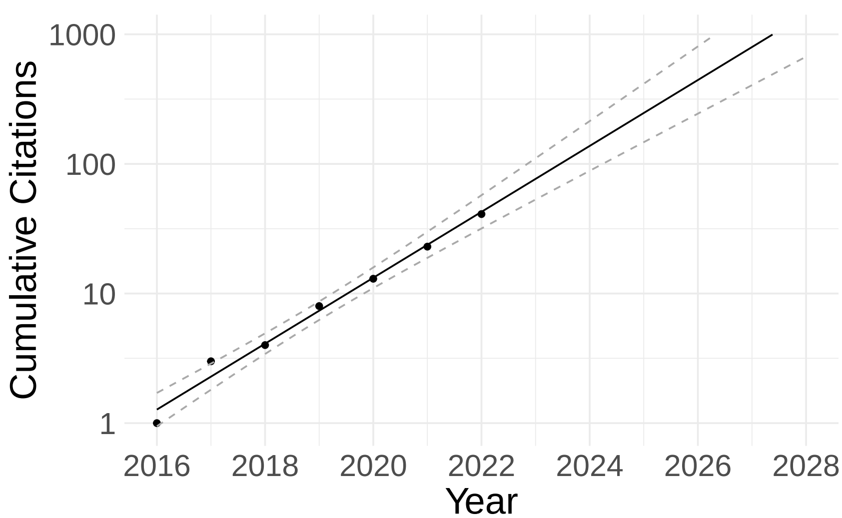


Figure 2: The evolution of cumulative citation count. Dots: data points, according to Google Scholar. Solid line: fitted values. Dashed lines: 95% confidence interval. The fitted model is: $\ln(\text{Cumulative Citations}) = 0.241^{*} + 0.585^{***}\,(\text{Year} - 2016)$, with $R^2 = 0.985$.

F Co-authors

Below is the list of my co-authors affiliated with academic institutions.

1. Efstathios Avdis, Associate Professor of Finance at the University of Alberta. We have collaborated on [6] and the work in progress extending it (see Section E).

2. Naveen Gondhi, Associate Professor of Finance at INSEAD. We co-authored [1]. At the time of collaboration, we were both assistant professors at INSEAD.

3. Christoph Frei, Professor of Mathematics at the University of Alberta. We collaborate on work in progress extending [6] (see Section E.4).

4. Raphael Huwyler, PhD student in Mathematics at the University of Alberta. We collaborate on work in progress extending [6] (see Section E.4).

5. John Kuong, Assistant Professor of Finance at INSEAD. We co-authored the papers [1] and [4].

6. Semyon Malamud, Associate Professor of Finance at the École Polytechnique Fédérale de Lausanne. We co-authored the papers [3], [5] and [7].

7. Alberto Teguia, Assistant Professor of Finance at the Sauder School of Business, University of British Columbia. We co-authored the papers [3], [5] and [7].

8. Bart Yueshen, Assistant Professor of Finance at Singapore Management University. We co-authored [2]. At the time of collaboration, we were both assistant professors at INSEAD.

I also collaborated with co-authors working in the industry. Florent Gallien and Serge Kassibrakis listed below, were instrumental in getting access to the proprietary data we use in [5].

9. Florent Gallien, Head of Research at Swissquote.

10. Serge Kassibrakis, Head of Quantitative Asset Management at Swissquote.

G Evolution of my research portfolio

In this section, I provide some background information on the history of my papers. Three of my published papers, [2], [3], and [4], have evolved from the three chapters of my PhD dissertation.[35] In particular, [3] has resulted from a merger between my job market paper (Chapter 1 of the thesis) and an independent and highly related paper by Semyon Malamud and Alberto Teguia.[36] In addition to [3], this merger has also produced the

[35]My PhD dissertation is publicly available at the online archive of PhD theses for the London School of Economics here.

[36]See Malamud and Teguia (2017), available here.

working paper [7]. Of course, both [3] and [7] are more than the sum of the two earlier papers. The fruitful collaboration that started after we joined forces with Semyon and Alberto has produced new theoretical results in both [3] and [7], and new empirical results in [3].

Paper [4] has evolved from Chapter 2 of my dissertation, originally solo-authored. I had very limited time bandwidth around the birth of my third kid, so I was looking to expand it by collaborating with someone else on my solo paper. I naturally thought of John Kuong as a co-author, as the idea for [4] was inspired by John's internal job market paper presentation at LSE, where John and I both studied. Together with John, we've found the right positioning for the paper, expanded the theoretical analysis, and added the empirical motivation. These efforts resulted in a publication in the Journal of Financial Economics.

Paper [2] has evolved from Chapter 3 of my dissertation, originally written with Ji Shen, my classmate from the LSE PhD program. Unfortunately, after Ji graduated from LSE, he stopped responding to my emails and stopped contributing to the paper.[37] I was looking for someone to replace him. Luckily, as a colleague, I had Bart Yueshen, who has related research interests and expertise. Together with Bart, we modified the model to better fit the application, expanded the theoretical analysis, and added the calibration exercise. The paper was published in the Review of Financial Studies.

For the sake of full transparency, I also note that I joined [5] at a relatively advanced stage when the working paper was available.[38] Semyon and Alberto, my co-authors on [3] and [7] were looking for someone to replace one their co-authors who has left academia. Since I joined, we significantly changed the model and theoretical analysis, adjusted the empirical analysis to test new theoretical results, and added a new calibration exercise. The paper is currently under review at the Journal of Financial Economics (following the prior reject and resubmit decision).

[37]This is the reason why his name is the last on the paper, deviating from the alphabetical order customary in Finance.

[38]See the working paper version before I joined here.

H List of papers

Published papers

[1] Sergei Glebkin, Naveen Gondhi, and John Chi-Fong Kuong, Funding Constraints and Informational Efficiency, *Review of Financial Studies, 2021*

[2] Sergei Glebkin, Bart Zhou Yueshen, and Ji Shen, Simultaneous Multilateral Search, *Review of Financial Studies, 2023*

[3] Sergei Glebkin, Semyon Malamud, and Alberto Teguia, Illiquidity and Higher Cumulants, *Review of Financial Studies, 2023*

[4] Sergei Glebkin and John Chi-Fong Kuong, When Large Traders Create Noise, *Journal of Financial Economics, 2023*

Under revision

[5] Florent Gallien, Sergei Glebkin, Serge Kassibrakis, Semyon Malamud, and Alberto Teguia, Price Formation in the Foreign Exchange Market, *reject and resubmit at the Journal of Financial Economics,* resubmitted

Working papers

[6] Efstathios Avdis and Sergei Glebkin, CHILE, *finalizing for submission at the Journal of Finance.*

[7] Sergei Glebkin, Semyon Malamud, and Alberto Teguia, Strategic Trading with Wealth Effects

VI Supplemental evidence: teaching

A Teaching load and evaluations

Course		#Units		Rating
Year 2016/2017				
MBA programme				
Corporate Financial Policy		15		3.96
Corporate Financial Policy		15		4.19
	Total:	30	*Avg.*	4.08
Year 2017/2018				
MBA programme				
Corporate Financial Policy		20		4.51
Corporate Financial Policy		20		4.31
Corporate Financial Policy		20		4.07
Corporate Financial Policy		20		4.33
	Total:	80	*Avg.*	4.31
PhD programme				
Continuous Time Finance A		10		-
	Total:	10		-
Year 2018/2019				
MBA programme				
Corporate Financial Policy		20		3.61
Corporate Financial Policy		20		3.36
Corporate Financial Policy		20		3.95
Corporate Financial Policy		20		3.73
FinTechs		1.43		3.5
FinTechs		1.43		3.33
	Total:	82.83	*Avg.*	3.58
PhD programme				
Continuous Time Finance A		10		-
Continuous Time Finance B		10		-
	Total:	20		-
Year 2019/2020				
MBA programme				
Corporate Financial Policy (Sessions 1-7)		10		4.49
Corporate Financial Policy (Sessions 1-7)		10		4.34
	Total:	20	*Avg.*	4.42
PhD programme				
Continuous Time Finance A		10		-
	Total:	10		-

Course		#Units	Rating
Year 2020/2021			
MBA programme			
Corporate Financial Policy		20	4.72
Corporate Financial Policy		20	4.72
Corporate Financial Policy		20	4.67
	Total:	60	*Avg.* 4.70
PhD programme			
Continuous Time Finance A		10	-
Continuous Time Finance B		10	-
	Total:	20	-
Year 2021/2022			
MBA programme			
Corporate Financial Policy		20	4.41
Corporate Financial Policy		20	4.26
Corporate Financial Policy		20	4.23
Corporate Financial Policy		20	4.23
Corporate Financial Policy		20	4.59
	Total:	100	*Avg.* 4.34
PhD programme			
Continuous Time Finance A		10	-
	Total:	10	-
Year 2022/2023			
PhD programme			
Continuous Time Finance A		10	-
Continuous Time Finance B		10	-
	Total:	20	-
Year 2023/2024, including scheduled			
MBA programme			
Corporate Financial Policy		20	4.30
Corporate Financial Policy		20	4.39
Corporate Financial Policy		20	4.55
Corporate Financial Policy		20	4.42
	Total:	80	*Avg.* 4.42
PhD programme			
Continuous Time Finance A		10	-
	Total:	10	-

B Trading Games and Arbitrage Pricing Simulation: description

Introduction

What?
A trading game. You will trade some (fictitious) financial assets in an environment that is similar to (but simplified, for pedagogical purposes) a stock exchange, such as NYSE. The student with highest profit will get a **prize:**1) a box of chocolate 2) a place in the *hall of fame*: your name (and a photo, if you wish) will be on the first slide of our second class.

Why?
The main goal is to have fun. The game will also allow you to get familiar with some of the concepts we study in CFP. You will get **the full grade for participation** in each of the three games, **no matter how much trading profit you make**.

The rules of the game

In this game there are two periods and two financial assets. We look at two dates, today and one month later. The first asset is a *stock* of a fictitious firm CFP, Inc. We will refer to the stock by its fictitious ticker CFPY. The second asset is a contract that allows you to buy or sell the CFPY a month later at a price that is known today. You should remember from the class that such a contract is called a *forward contract.* The risk-free rate between today and one month later is assumed to be 0%.

Assets

Stock:
The price of CFPY is €100 per share today. One month later, there are only two possible outcomes. The price of CFPY can either go up to €140 with a probability of 0.5, or go down to €80 with a probability of 0.5. Of course, we will not wait for a month. Instead, I (the professor) will flip a coin. If the coin turns heads, the CFPY price a month from now is €140; if it turns tails, CFPY price a month from now is €80.

Forwards:

A forward contract takes the following form:

I commit to buy/sell 1 share of CFPY stock at the price of €F one month later.

To understand this contract, let's look at an example. Suppose Alice and Chuck enter a forward contract, in which Chuck commits to buy, and Alice commits to sell 1 share of CFPY stock at the price of F=115. One month later, Alice has to give Chuck 1 share of CFP stock. In return, Chuck has to pay Alice €115 as stated in the contract. The contract doesn't involve any payment today.

If the price of CFPY turns out to be €140 in one month, Chuck gets CFPY share worth €140 and needs to pay €115 for it as written in the contract. Therefore, he wins €25. Alice sells the stock of CFPY, which is worth €140, to Chuck at the price of €115. She loses €25. Similarly, if the price of CFPY turns out to be €80, Chuck loses €35 and Alice wins €35.

Trading

Today you can trade forward contracts, as described below. Your demand for the contract determines the *forward price F,* through the market clearing process described below.

To trade the forward contract, each of you can submit your orders in the following form. (See also a step-by-step guide with screenshots at the end of this document)

> *I commit to buy 1 CFPY stock in one month if the price F is below ___.*
>
> *I commit to sell 1 CFPY stock in one month if the price F is above ___.*

This type of order is usually called a limit order. It is the most widely used type of order in financial markets.

Market clearing

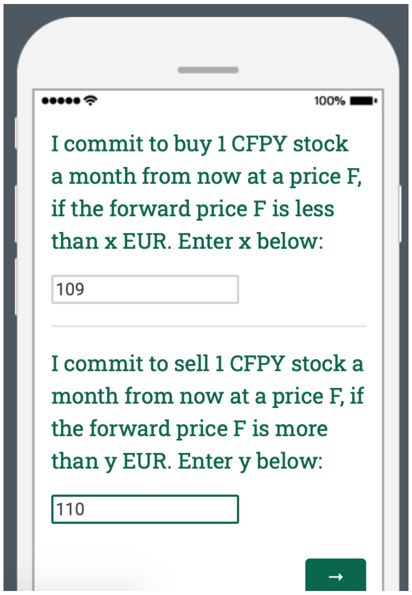
The rule for setting the price F is quite simple. I (the professor, and the market maker) will pick the right price such that half of the participants want to buy and the other half want to sell. If you are interested in the magic I do, more details are provided in the example below.

> Suppose that Alice, Bob and Chuck submit the following orders.
>
> Alice commits to buy 1 unit of CFPY if forward price is lower than 109
> Alice commits to sell 1 unit of CFPY if forward price is higher than 110
> Bob commits to buy 1 unit of CFPY if forward price is lower than 100
> Bob commits to sell 1 unit of CFPY if forward price is higher than 104
> Chuck commits to buy 1 unit of CFPY if forward price is lower than 105
> Chuck commits to sell 1 unit of CFPY if forward price is higher than 106
>
> Suppose I set the forward price F to be 107. Then Bob and Chuck will sell 1 unit of CFPY, and only Alice will be willing to buy. Two participants want to sell, whereas only one wants to buy. The price is too high.
>
> In this example, the market-clearing forward price is 105.5. At this price Chuck does nothing, Bob sells one unit of CFPY and Alice buys 1 unit.

Step by step guide on how to play the game.

Step 1. Go to the course website on LMS, find the link to Trading Game 1 under *Modules/Session 01* or *Assignments*.

Step 2. Enter your trading strategy. The screenshot below corresponds to Alice's strategy. (Alice commits to buy 1 unit of CFPY if the forward price is lower than 109. Alice commits to sell 1 unit of CFPY if forward price is higher than 110)



Step 3. Click on "SUBMIT" (not the "next" button on LMS), and you will see "We thank you for your time spent taking this survey. Your response has been recorded."

Now it's time to move on to Trading Game 2.

Trading Game 2

Introduction

This game is similar to the previous trading game. The difference is that now you will be able to trade both forward contracts and the CFPY stock. This will allow you to use more sophisticated trading strategies.

The rules of the game

In this game there are two periods and two financial assets. We look at two dates, today and one month later. The first asset is a *stock* of a fictitious firm CFP, Inc. We will refer to the stock by its fictitious ticker CFPY. The second asset is a contract that allows you to buy or sell the CFPY a month later at a price that is known today. You should remember that such a contract is called a *forward contract.* The risk-free rate between today and one month later is assumed to be 0%.

If there are several students with the same highest profit, I choose one winner at random.

Assets (same as in Trading Game 1)

Stock:

The price of CFPY is €100 per share today. One month later, there are only two possible outcomes. The price of CFPY can either go up to €140 with probability of 0.5, or go down to €80 with probability of 0.5. Of course, we will not wait for a month. Instead, I will flip a coin. If the coin turns heads, the CFPY price a month from now is €140; if it turns tails, CFPY price a month from now is €80.

Forwards:

A forward contract takes the following form:

I commit to buy/sell 1 share of CFPY stock at the price of €F one month later.

To understand this contract, let's look at an example. Suppose Alice and Chuck enter a forward contract, in which Chuck commits to buy, and Alice commits to sell 1 share of CFPY stock at the price of F=115. One month later, Alice has to give Chuck 1 share of CFP stock. In return, Chuck has to pay Alice €115 as stated in the contract. The contract doesn't involve any payment today.

If the price of CFPY turns out to be €140 in one month, Chuck gets CFPY share worth €140 and needs to pay €115 for it as written in the contract. Therefore, he wins €25. Alice sells the stock of CFPY, which is worth €140, to Chuck at the price of €115. She loses €25. Similarly, if the price of CFPY turns out to be €80, Chuck loses €35 and Alice wins €35.

Trading

For Trading Game 2 you can trade *both forward contracts and CFPY stocks*. We assume the stock is traded on a separate exchange, and the price today and in the future is not affected by our trading. In contrast, the forward contracts are traded among you only, so the *forward price F is determined by* your demand for the forward contracts, through the market clearing process described below.

Each of you can submit orders in the following form. (See also a step-by-step guide with screenshots at the end of this document)

> *If the price F is below ___, I buy 1 CFPY stock today at price* €100 */ sell 1 CFPY stock today at price* €100 */ do not trade CFPY stock today (choose one option)*, and *I commit to buying 1 CFPY stock in one month at price €F.*
>
> *If the price F is above ___, I buy 1 CFPY stock today at price* €100 */ sell 1 CFPY stock today at price* €100 */ do not trade CFPY stock today (choose one option)*, and *I commit to selling 1 CFPY stock in one month at price €F.*

In real life, such an order would be implemented through limit orders and trading algorithms.

An example

For example, suppose Bob submits the following order:

> *If the price F is below 90, I do not trade CFPY stock today*, and *I commit to buying 1 CFPY stock in one month at price €F.*
>
> *If the price F is above 110, I buy 1 CFPY stock today at price* €100, and *I commit to selling 1 CFPY stock in one month at price €F.*

Suppose the forward price is F=€115. Let's look again at Bob's order:

> *If the price F is below 90 (not true, since F*=115>90*) I do not trade CFPY stock today*, and *I commit to buying 1 CFPY stock in one month at price €F.*
>
> *If the price F is above 110 (true, since F*=115>110*),* ***I buy 1 CFPY stock today at price* €100, and *I commit to selling 1 CFPY stock in one month at price €F.***

Only the part of the order highlighted in black will be executed. Therefore, Bob buys 1 CFPY stock today at price €100 and commits to selling 1 CFPY stock in one month at price €115.

Suppose CFPY price rises to €140. Bob purchased the stock at €100, therefore he earns €140-€100=€40 from trading stock. He also committed to selling CFPY at €115 in his forward contract. Therefore, he loses €140-€115=€25 there. The total profit is €40-€25=€15.

Similarly, if CFPY price drops to €80, Bob loses €100-€80=€20 in trading the stock and earns €115-€80=€35 from the forward contract. The total profit is €35-€20=€15.

Market clearing

The rule for setting the price F is the same as before. I will pick the right price such that half of the participants want to buy and the other half want to sell.[1]

Step by step guide on how to play the game.

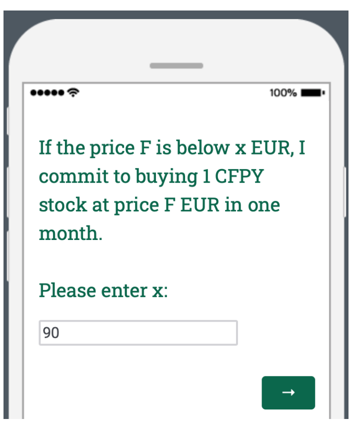
Step 1. Go to the course website on LMS, find the link to Trading Game 2 under *Modules/Session 01* or *Assignments*.

Step 2. Enter your trading strategy. The screenshot below corresponds to Bob's strategy in the example above

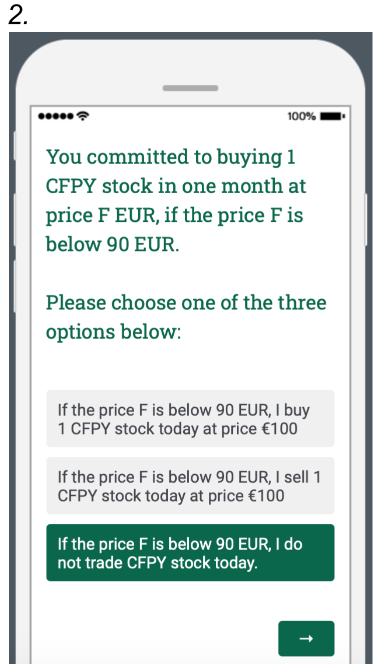
If the price F is below €90, I do not trade CFPY stock today, and *I commit to buying 1 CFPY stock in one month at price €F.*

If the price F is above €110, I buy 1 CFPY stock today at price €100, and *I commit to selling 1 CFPY stock in one month at price €F.*

1.



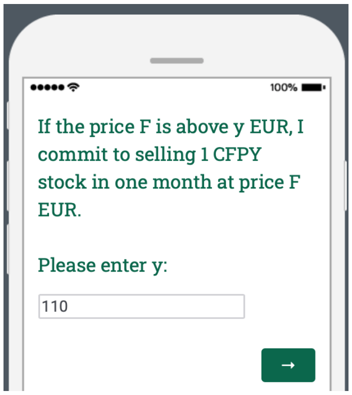
2.

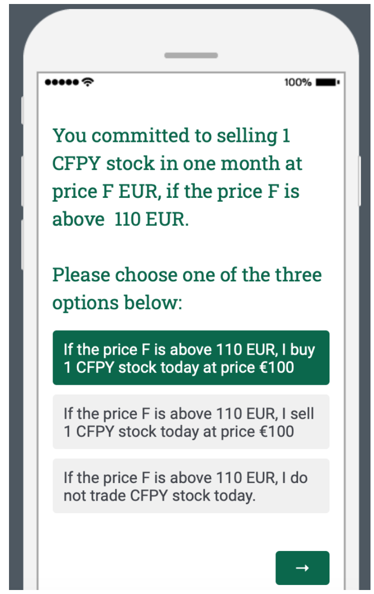


3.

4.

[1] Strictly speaking, the market clearing price F* is such that for any F<F* there are more participants who want to buy, and for any F>F* there are more participants who want to sell.





Step 3. Click on “SUBMIT” (not the “next” button on LMS), and you will see “We thank you for your time spent taking this survey. Your response has been recorded.”

Now it’s time to move on to Trading Game 3.

Trading Game 3

Introduction

This game is similar to Trading Game 2, with only one extra step. Now you can scale up your trading strategy by placing multiple identical orders to raise the stakes. Isn't that exciting?

The rules of the game (skip to "Trading" if you have played game 2)

In this game there are two periods and two financial assets. We look at two dates, today and one month later. The first asset is a *stock* of a fictitious firm CFP, Inc. We will refer to the stock by its fictitious ticker CFPY. The second asset is a contract that allows you to buy or sell the CFPY a month later at a price that is known today. You should remember that such a contract is called a *forward contract.* The risk-free rate between today and one month later is assumed to be 0%.

If there are several students with the same highest profit, I choose one winner at random.

Assets (same as in the 1st game)

Stock:

The price of CFPY is €100 per share today. One month later, there are only two possible outcomes. The price of CFPY can either go up to €140 with probability of 0.5, or go down to €80 with probability of 0.5. Of course, we will not wait for a month. Instead, I will flip a coin. If the coin turns heads, the CFPY price a month from now is €140; if it turns tails, CFPY price a month from now is €80.

Forwards:

A forward contract takes the following form:

I commit to buy/sell 1 share of CFPY stock at the price of €F one month later.

To understand this contract, let's look at an example. Suppose Alice and Chuck enter a forward contract, in which Chuck commits to buy, and Alice commits to sell 1 share of CFPY stock at the price of F=115. One month later, Alice has to give Chuck 1 share of CFP stock. In return, Chuck has to pay Alice €115 as stated in the contract. The contract doesn't involve any payment today.

If the price of CFPY turns out to be €140 in one month, Chuck gets CFPY share worth €140 and needs to pay €115 for it as written in the contract. Therefore, he wins €25. Alice sells the stock of CFPY, which is worth €140, to Chuck at the price of €115. She loses €25. Similarly, if the price of CFPY turns out to be €80, Chuck loses €35 and Alice wins €35.

Trading

Trading is now divided into two steps. First, you tell me about your order as in Trading Game 2. Then I will ask you how many identical orders you would like to submit.

The first step is exactly the same as in Trading Game 2. You can trade *both forward contracts and CFPY stocks*. We assume the stock is traded on a separate exchange, and the price today and in the future is not affected by your trading. In contrast, the forward contracts are traded among you only, *so the forward price F is determined by your demand for the forward contracts*, through the market clearing process described below.

Each of you can submit orders in the following form. (See also a step-by-step guide with screenshots at the end of this document)

> *If the price F is below ___, I buy 1 CFPY stock today at price* €100 */ sell 1 CFPY stock today at price* €100 */ do not trade CFPY stock today (choose one option)*, and *I commit to buying 1 CFPY stock in one month at price €F.*
>
> *If the price F is above ___, I buy 1 CFPY stock today at price* €100 */ sell 1 CFPY stock today at price* €100 */ do not trade CFPY stock today (choose one option)*, and *I commit to selling 1 CFPY stock in one month at price €F.*

In real life, such an order would be implemented through limit orders and trading algorithms.

In the second step, you can choose how much you want to scale up the strategy above. You can submit up to 100 orders submitted in step 1.

However, there is an additional limitation. The more risky your order is, the fewer number of orders you can trade. In real life you can trade more stocks and forwards using the financing from your broker-dealer. However, they impose risk limits (or margin constraints) to make sure you will not lose too much money. In our game, the risk limit on the number of orders you can submit is such that you cannot lose more than 100 EUR in the game.

I provide you an Excel spreadsheet to compute the risk limit for you so that you can test how much you can scale up your strategy. This limit will be automatically imposed when you submit your order on Qualtrics.

An example

For example, suppose Bob submits the following order:

> *If the price F is below 90, I do not trade CFPY stock today*, and *I commit to buying 1 CFPY stock in one month at price €F.*
>
> *If the price F is above 110, I buy 1 CFPY stock today at price* €100, and *I commit to selling 1 CFPY stock in one month at price €F.*

Suppose the forward price is F=€115. Let's look again at Bob's order:

If the price F is below 90 (not true, since F=115>90*) I do not trade CFPY stock today*, and *I commit to buying 1 CFPY stock in one month at price €F.*

If the price F is above 110 (true, since F=115>110*),* ***I buy 1 CFPY stock today at price*** **€100, and *I commit to selling 1 CFPY stock in one month at price* €*F.***

Only the part of the order highlighted in black will be executed. Therefore, Bob buys 1 CFPY stock today at price €100 and commits to selling 1 CFPY stock in one month at price €115.

Suppose CFPY price rises to €140. Bob purchased the stock at €100, therefore he earns €140-€100=€40 from trading stock. He also committed to selling CFPY at €115 in his forward contract. Therefore, he loses €140-€115=€25 there. The total profit is €40-€25=€15.

Similarly, if CFPY price drops to €80, Bob loses €100-€80=€20 in trading the stock and earns €115-€80=€35 from the forward contract. The total profit is €35-€20=€15.

To summarize, Bob's profit is €15 no matter whether the stock price goes up or down. Note that this is Bob's profit from only one order. If Bob chose to submit 5 identical orders, his profit will be €75 no matter whether the stock price goes up or down (provided that the price F=€115).

Market clearing

The rule for setting the price F is the same as before. I will pick the right price such that half of the participants want to buy and the other half want to sell.[2]

Step by step guide on how to play the game.

Step 0. Design your trading strategy. Input it into the excel spreadsheet provided and check how much you can scale it up.

Take Bob's strategy from the example above:

If the price F is below €90, I do not trade CFPY stock today, and I commit to buying 1 CFPY stock in one month at price €F.

If the price F is above €110, I buy 1 CFPY stock today at price €100, and I commit to selling 1 CFPY stock in one month at price €F.

	A	B	C
1			
2	If the price F is below x, I commit to buying 1 CFPY stock at price F EUR in one month.	Enter x here (a number):	90
3	and I buy / do not trade / sell 1 CFPY stock at price €100.	Enter "1" if you buy, "0" if you do not trade, and "-1" if you sell	0
4			
5	If the price F is above y, I commit to selling 1 CFPY stock at price F EUR in one month.	Enter y here (a number):	110
6	and I buy / do not trade / sell 1 CFPY stock at price €100.	Enter "1" if you buy, "0" if you do not trade, and "-1" if you sell	1
7			
8			
9		Maximum number of orders you can submit:	10

[2] Strictly speaking, the market clearing price F* is such that for any F<F* there are more participants who want to buy, and for any F>F* there are more participants who want to sell.

In our example Bob will be able to scale up his trading strategy 10 times.

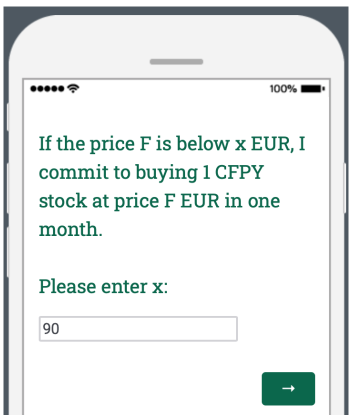
Step 1. Go to the course website on LMS, find the link to Trading Game 3 under *Modules/Session 01* or *Assignments*.

Step 2. Enter your trading strategy. The screenshot below corresponds to Bob's strategy in the example above

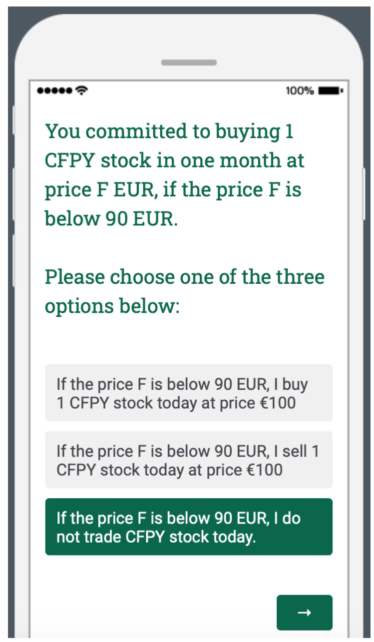
If the price F is below €90, I do not trade CFPY stock today, and *I commit to buying 1 CFPY stock in one month at price €F.*

If the price F is above €110, I buy 1 CFPY stock today at price €100, and *I commit to selling 1 CFPY stock in one month at price €F.*

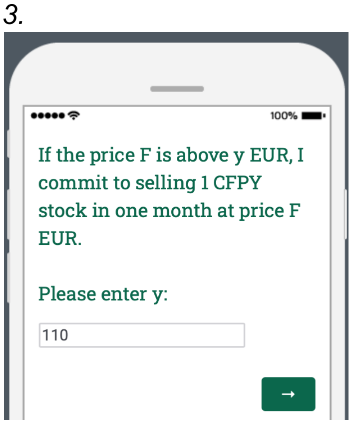
1.



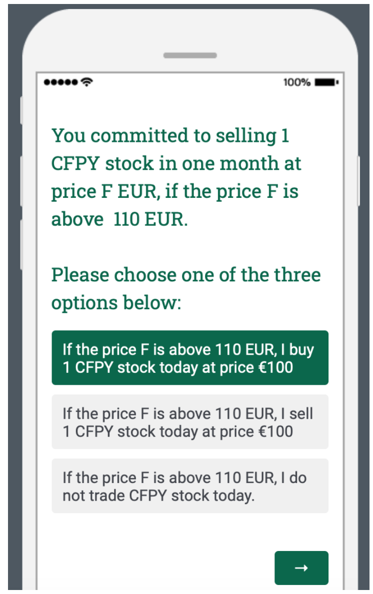
2.



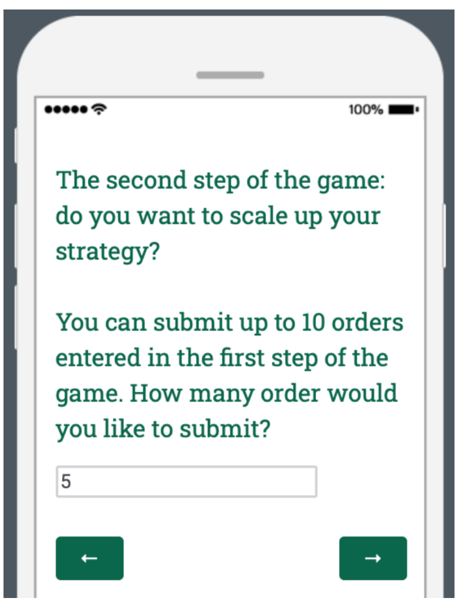
3.



4.



Step 3. Decide how much to scale up your strategy.
Bob can submit up to 10 orders entered in the previous step. He chooses to submit 5.



Step 4. Click on “SUBMIT” (not the “next” button on LMS), and you will see “We thank you for your time spent taking this survey. Your response has been recorded.”

Congratulations! You have completed all three trading games!

Session 2: Forward and Option Contracts

Corporate Financial Policy
INSEAD MBA Program
Professor Sergei Glebkin

Plan for today

I. Derivatives and their use in corporate finance

- Forwards
  - Debrief of the trading games
- Introduction to options
  - Definition, terminology, payoff diagrams
  - Uses

Forwards

- **Definition:** a contract to buy (or sell) an asset at a fixed time in the future at a specified price agreed upon today.
- **Terminology:** forward (delivery) price, underlying asset, expiration date, long (short) position
- **Uses.** Weapons to defeat risk
- **Pricing.** CFP, not FMV way: replication, not NPV
  - $\boxed{F = S_0(1+r)^T}$, called fair price
  - Replicating portfolio: buy the underlying by borrowing at risk-free rate r (amount of cash to borrow: S_0)

Forwards: trading games debrief

Consider a one month forward contract on a fictitious stock CFPY. The price of CFPY is 100 now and either 140 or 80 a month from now with equal probability. Assume risk-free rate is 0%. What the forward price should be?

How can we get to know your opinion?

1. Ask you: boring; your answers are not credible (talk is cheap)
2. Make you trade: exciting; answers are credible (you put your (fictitious) money where your mouth is)

Forwards: trading games debrief

Consider a one month forward contract on a fictitious stock CFPY. The price of CFPY is 100 now and either 140 or 80 a month from now with equal probability. Assume risk-free rate is 0%. What the forward price F should be equal to?

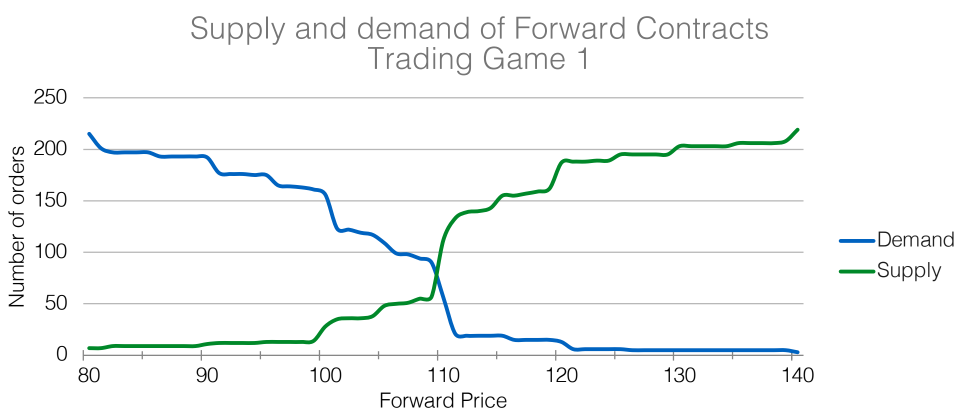
In financial markets you can express your opinion!

If you think forward price should be 110, then

- you will be happy to buy (enter long forward contract) if market price F is <110.
- you will be happy to sell (enter short forward contract) if market price F is >110.
- market price reflects average (median) opinion of all traders

Trading Game 1

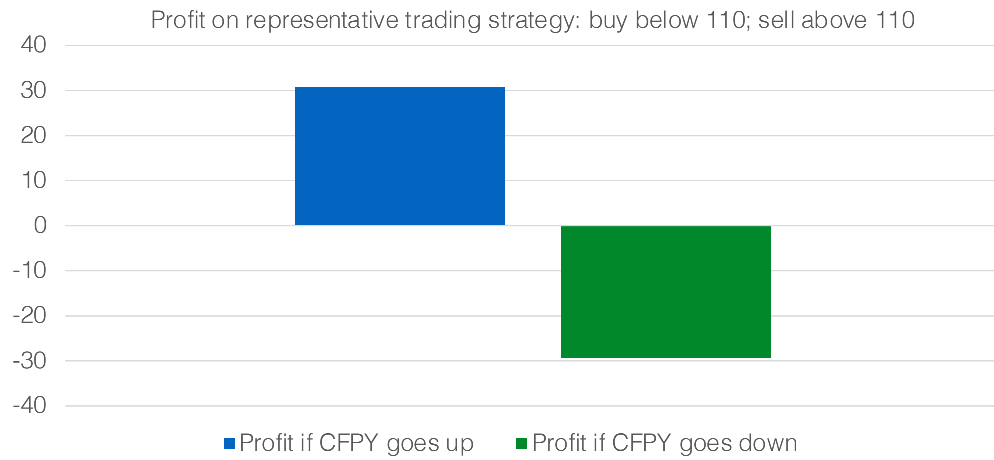
Only forwards on CFPY are traded



- **Market price**$= \mathbf{109.5} \approx \mathbf{110} \Rightarrow$ your average opinion: forward price is equal to expected CFPY price in one month $(110 = 0.5 \cdot 140 + 0.5 \cdot 80)$
- **Buying below 110 and/or selling above 110 is a popular strategy:** notice jumps in demand and supply at $F = 110$

Trading Game 1

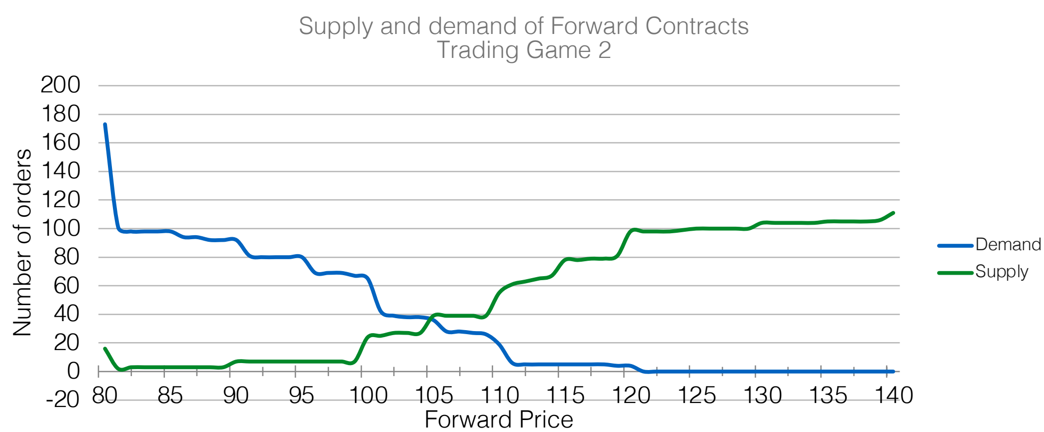
Only forward contracts on CFPY are traded



- The representative trading strategy is *risky.* If you are unlucky, you can lose money.
- In this game, you can only win by luck.

Trading Game 2

Stocks and forwards on CFPY are traded



- **New popular opinion emerges:** forward price should be 100. (Notice jumps in demand and supply at $F = 100$).
- **Market price=105.** Market price moves towards 100. But not all the way down: those thinking price F should be 100 cannot (yet) express their opinion strongly.

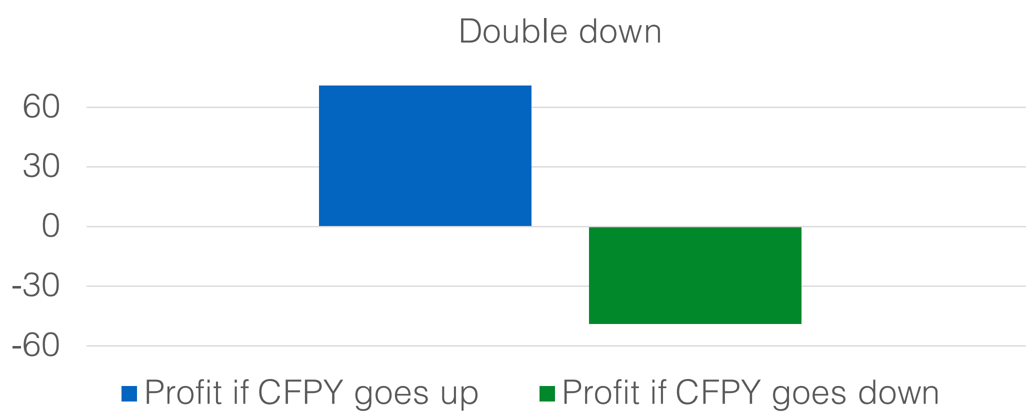
Trading Game 2

Stocks and forwards on CFPY are traded

Two popular strategies:

1. Double down

- if $F < 110$: buy CFPY forward, and buy CFPY spot
- if $F > 110$: sell CFPY forward, and sell CFPY spot



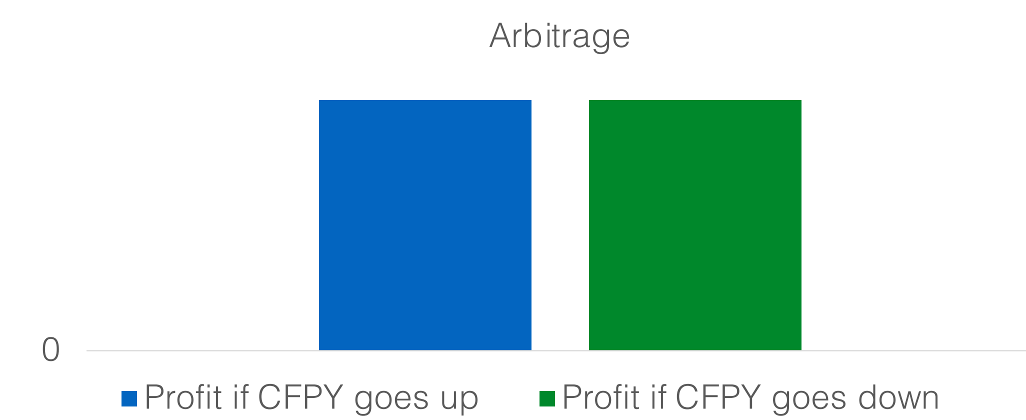
Trading Game 2

Stocks and forwards on CFPY are traded

Two popular strategies:

2. Arbitrage

- if $F < 100$: buy CFPY forward, and sell CFPY spot
- if $F > 100$: sell CFPY forward, and buy CFPY spot

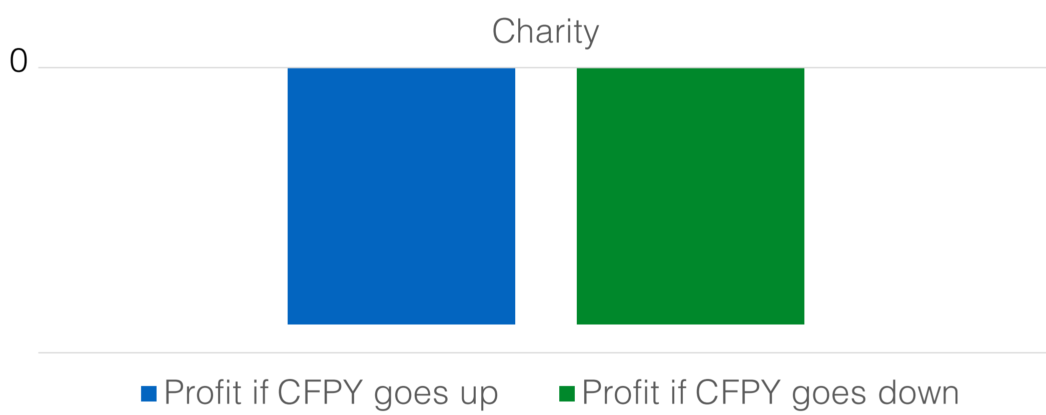


A note of caution

Some of you used the following strategy

3. Charity

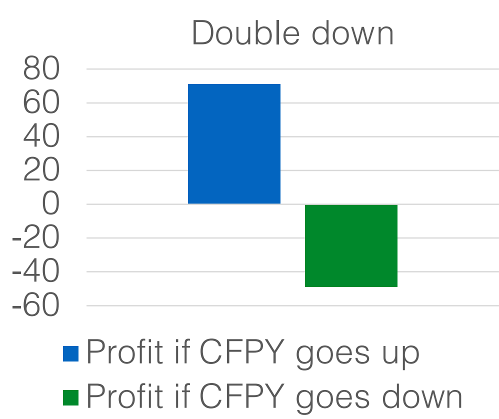
- if $F < 100$: sell CFPY forward, and buy CFPY spot
- if $F > 100$: buy CFPY forward, and sell CFPY spot

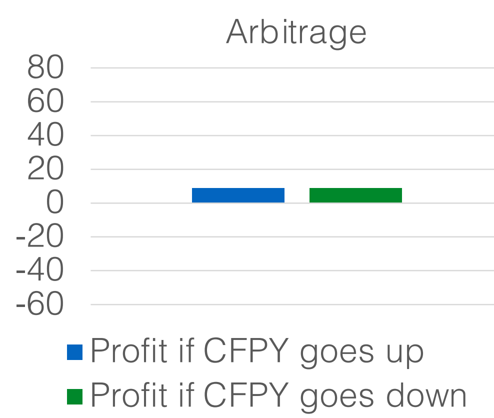


Trading Game 2

Stocks and forwards on CFPY are traded

Two popular strategies:





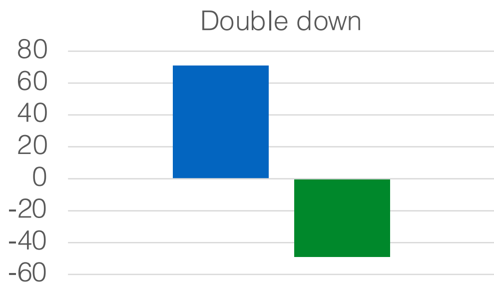
- Double down: risky. Can earn 75; may also lose 45 if unlucky.
- Arbitrage: **riskless profit** of 5.

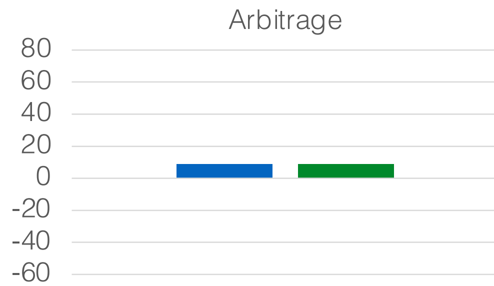
Trading Game 3

Stocks and forwards are traded. Risk limits.

New element in the game:

- Can scale up trading strategy up to 100 times.
- But the maximum loss cannot exceed 100 euros (risk limit)



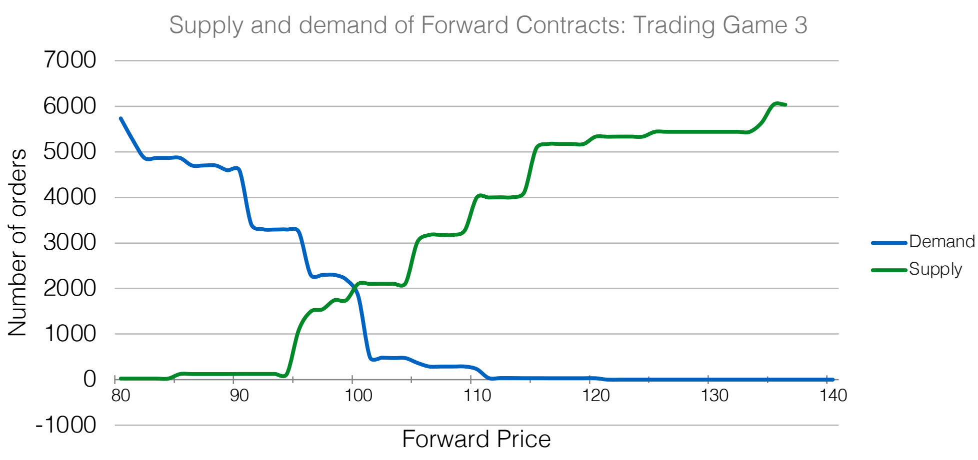


Double down: maximum loss is 45. Can only be scaled up 2x

Arbitrage: no loss. Can be scaled up 100x

Trading Game 3

Stocks and forwards are traded. Risk limits.



- **Big jumps in demand and supply around $F = 100$.** Because arbitrageurs can scale up their strategies a lot. Their opinion dominates the market.
- **Market price=100.** Market price is equal to the theoretical price derived the session 1!

D The Case of Square Inc's Valuation in 2014

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Case Study

Square Inc.'s Valuation in 2014

07/2019-6385-Ed

This case study was written by Lily Fang, Professor of Finance, Sergei Glebkin, Assistant Professor of Finance, and John Kuong, Assistant Professor of Finance, all at INSEAD. It is intended to be used as a basis for class discussion rather than to illustrate either effective or ineffective handling of an administrative situation.

In October 2014, Square Inc., the payment firm founded by Twitter co-founder Jack Dorsey, raised $150 million "Series E" funding[1] from a consortium of investors led by the Singapore Government's investment arm GIC and Goldman Sachs, a previous investor in Square Inc.[2] In exchange, the investors received 9.7 million shares, priced at $15.46 per share. Prior to this funding, Square Inc. had 378.3 million shares outstanding, hence the investors in this funding round received a 2.5% ownership stake in the firm (9.7/(378.3+9.7)).

About Square Inc.

Square Inc. was founded in February 2009 by Twitter co-founder Jack Dorsey. The initial idea of a payment processing firm came to Dorsey when his friend Jim McKelvey, an artist based in St. Louis, was unable to complete the sale of one of his artworks because he could not accept credit card payment. Messieurs Dorsey and McKelvey co-founded Square Inc. on the hunch that allowing millions of small merchants to accept credit card payments could be a viable and valuable business.

But the payments industry was becoming increasingly competitive, with giant incumbents such as banks and credit card companies, and deep-pocketed tech heavyweights such as PayPal. Unbeknownst to Messieurs Dorsey and McKelvey at the time of Square's founding, the competition was about to intensify with the entry of Apple, which released the first Apple Pay app also in October 2014, just before Square's $150m Series E funding round.

Square had accumulated losses since its start, and prior to the 2014 Series E funding those losses had mounted: it had burned through roughly $500 million raised in previous rounds. The $150 million cash infusion was considered a "life line" by the *Wall Street Journal*.

According to tech insiders, the unusual investor composition of the new funding round – from which marque venture capitalists (VCs) from Silicon Valley were conspicuously absent – indicated that top-tier VCs doubted Square's growth potential or valuation, or both.[3]

Questions

1. Assuming that the Series E investors received common shares, and that all other prior investors also have common shares, what is the implied valuation of Square Inc. after its Series E funding round? The financial press, including the *Wall Street Journal*, *Fortune*, *Bloomberg*, and the *Economist*, has reported that the firm is worth $6 billion.[4] Can you square (no pun intended) your calculation with these reports?

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1 In venture financing, funding rounds are referred to as Series A (the first round of VC investments), Series B (the second round of VC investment), etc. Square's Series E round in Oct 2014 is its 5th capital infusion.

2 https://www.wsj.com/articles/square-gets-150-million-lifeline-1412639052

3 *Ibid.*

4 https://www.wsj.com/articles/square-gets-150-million-lifeline-1412639052.; http://fortune.com/2014/10/06/square-worth-6-billion-after-latest-150-million-fundraising-round/; https://www.bloomberg.com/news/articles/2014-08-28/square-said-in-talks-for-funding-at-6-billion-valuation; https://www.economist.com/news/finance-and-economics/21678809-profitless-payment-firm-goes-public-swiped.

2. As it turns out, VCs do not invest in common shares of companies. Their shares are a special class of shares known as "preferred shares". The most common type of preferred shares in VC investing is called "convertible preferred". These have a unique feature called "liquidation preference", which works as follows:

   When the company is liquidated, acquired by another company, or goes public, investors holding preferred shares with the liquidation preference have the following two options:

   a. Claim back their principle (with no interest). They will be paid before other investors are paid.

   b. Convert their preferred shares into common shares. They will get one common share for one preferred share (the conversion ratio is 1:1).

   As it turns out, GIC and Goldman Sachs' Series E investment in Square was structured as convertible preferreds. Assume all other investors held common shares, and that Square Inc. had no debt in October 2014.

   What is the payoff to Series E investors at exit, i.e. when Square is either liquidated, acquired by another company or goes public, as a function of Square Inc.'s total value (V)? Draw the payoff diagram.

3. If we assume that the $150 million Series E investors paid for preferred shares is a "fair value" (after all, these are smart, sophisticated investors), what is the correct implied fair valuation of Square Inc.?

   Assume that the risk-free rate is 3% per annum. For any embedded options, the time to maturity is 3 years, the typical VC investment horizon for a late-stage investment (see, for example, Metrick and Yasuda, 2010), and that the annual asset value volatility for a start up like Square is 90% (see Cochrane, 2005). In comparison, the annual volatility of the S&P 500 is around 30%.

4. Now draw the payoff diagram of *common* shareholders collectively (i.e., everyone other than the Series E investors) as a function of the total value (V) of Square Inc.

5. Suppose you were an early hire at Square Inc., and you have accumulated 100,000 units of the company's common shares as part of your compensation. If there is a grey market for Square Inc.'s shares and you can sell your stake for $1 million, would you be willing to sell?

References

Cochrane, John H. "The risk and return of venture capital." Journal of Financial Economics 75, no. 1 (2005): 3-52.

Metrick, Andrew, and Ayako Yasuda. "Venture capital and the finance of innovation." (2010), 2nd Edition (John Wiley & Sons).

E The Case of Square Inc: teaching slides

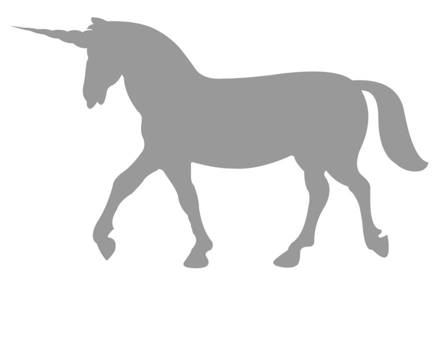
Session 7:
Square Inc case

Corporate Financial Policy
INSEAD MBA Program
Professor Sergei Glebkin

Unicorns

unicorn
/ˈjuːnɪkɔːn/
noun

- a mythical animal typically represented as a horse with a single straight horn projecting from its forehead.



Unicorns

unicorn
/ˈjuːnɪkɔːn/
noun

- a start-up company valued at more than a billion dollars, typically in the software or technology sector.

Plan for today

- Square Inc case
- Are unicorns overvalued?

Square Inc.'s Valuation in 2014

Bloomberg

Square Said in Talks for Funding at $6 Billion Valuation

The San Francisco-based company is seeking about $200 million, with some of the funding coming from the Government of Singapore Investment Corporation, said the person, who asked not to be identified because the matter is private.

Bloomberg, Aug 28, 2014.

WSJ

Square Gets Support of $150 Million

Singapore Leads Funding Round That Values Mobile-Payments Startup at **$6 Billion**

WSJ, Oct 6, 2014.

- Where does **$6bn** come from?
- Can we square this valuation with reality?

What newspapers report as value

For private startups such as Square newspapers report **post-money valuation (PMV)**

$$\begin{aligned}&\text{Post money valuation}\\&= \text{Total nuber of shares}\\&\cdot \text{Price per share in the latest round}\end{aligned}$$

In the case of Square:

$$\text{Post money valuation} = \$15.46 \cdot (378.3\text{m} + 9.7\text{m}) = \$\boldsymbol{6bn}$$

Moreover, newspapers equalize **post-money valuation** with **the value of the firm**

When is $\text{value} = \text{PMV}$?

Firm value is equal to post-money valuation **only if:**

1. A firm has no debt (PMV is a measure of equity value)
   - True for Square in 2014, and not uncommon for startups in general
2. Shares in latest round are identical to shares in previous rounds (PMV treats all shares equally)
   - Not true for Square in 2014, and generally not true for startups
   - Shares in later rounds typically have more attractive features

Square Case: what did VCs get?

At exit (i.e., when the company is liquidated, acquired by another company, or goes public) VCs can choose between two options:

A. Claim back their investment, in our case $\$150m$. They will be paid before other investors are paid.

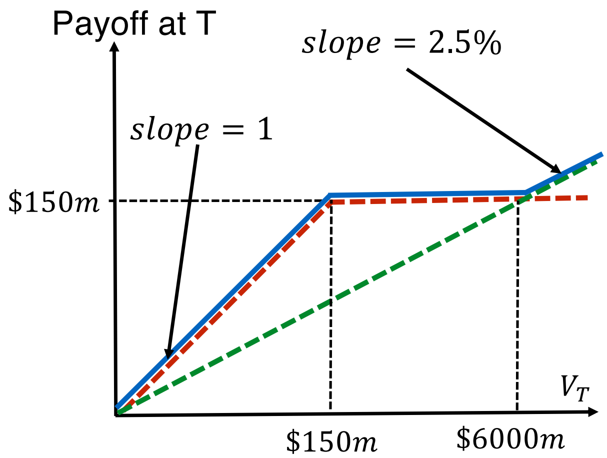
B. Convert their preferred shares into common shares. (the conversion ratio is 1:1).

Square Case: VCs payoff at exit

Denote V_T Square's value at exit. At exit VCs can choose between two options.

A. Claim back $\$150m$.

B. Convert their preferred shares into common shares.



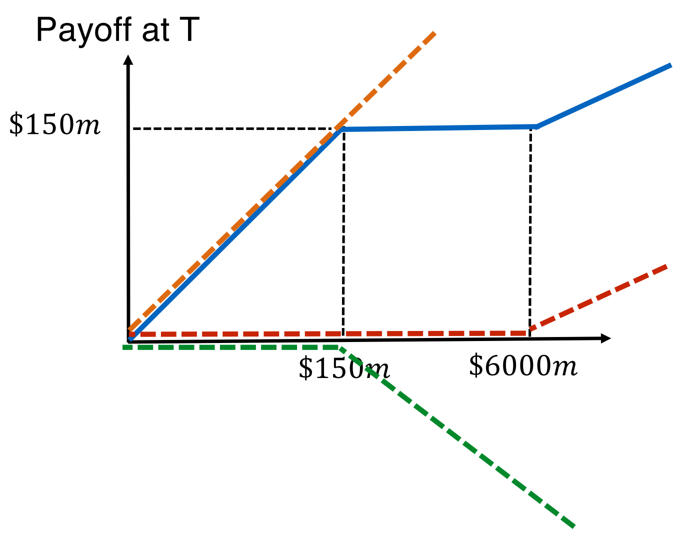
Red and green lines intersection:

$\$150m = 2.5\% \cdot V_T \Rightarrow V_T = \$6000m$

Payoff to VCs at exit

$$= \begin{cases} V_T & \text{if } V_T < \$150m \\ \$150m & \text{if } \$150m \leq V_T \leq \$6000m \\ 2.5\% \cdot V_T & \text{if } V_T > \$6000m \end{cases}$$

Square Case: VCs payoff at exit



Payoff to Series E investors at exit

$= V_T - C_T(150, V_T) + 0.025 \cdot C_T(6000, V_T)$

Key pricing equation

$150 = V - C(150, \boldsymbol{V}) + 0.025 \cdot C(6000, \boldsymbol{V})$

The value of Square Inc in 2014

- Denote $C^{BS}(K;V)$ Black-Scholes price of Call, with strike $\boldsymbol{K}$, price of underlying $\boldsymbol{V}$, time to maturity of **3 years**, risk-free rate of **3%** and volatility of **90%.**

- Solve in Excel for V:

$$150 = V - C^{BS}(150, V) + 0.025 \cdot C^{BS}(6000, V)$$
$$V = \$2.356bn$$

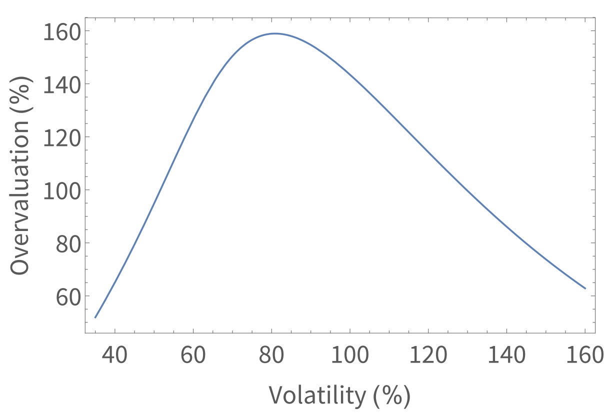
- Newspapers overvalue Square Inc by **154%!**

The value of Square Inc in 2014

- Define **overvaluation** as

$$\frac{Reported\ valuation}{Actual\ valuation} - 1 = \frac{6bn}{V} - 1$$

How sensitive is our estimate of overvaluation to our assumptions about σ?



Bottom line: for any reasonable assumption about volatility, the overvaluation is at least 50%!

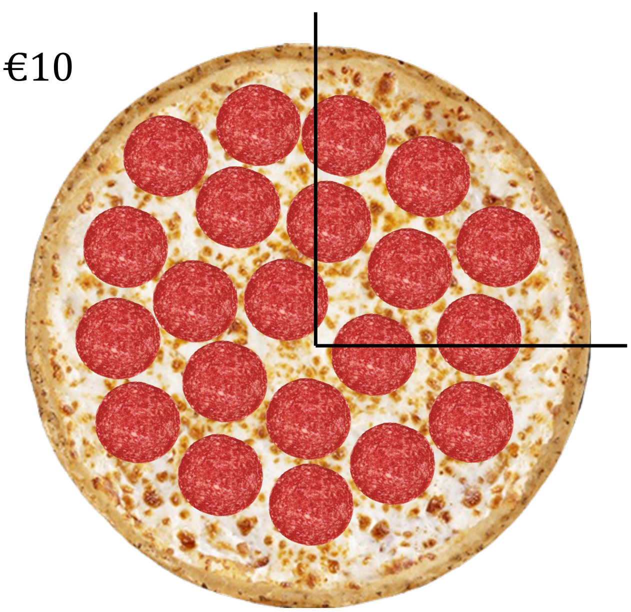
Overvaluation: illustration

$V_{pizza} = €10$

Suppose a startup is a pepperoni pizza…
To make a pizza you need to raise €5

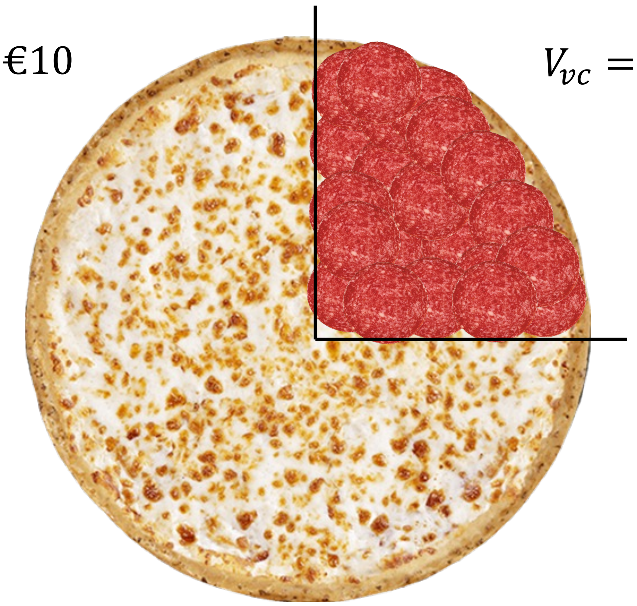
Overvaluation: illustration

$V_{pizza} = €10$



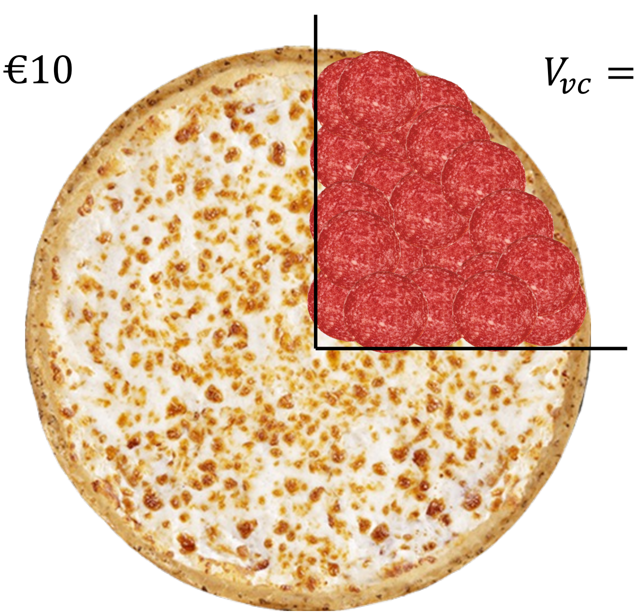
To raise €5 you sell a quarter of the pizza to VCs

Overvaluation: illustration



But you need to offer VCs a very special piece…

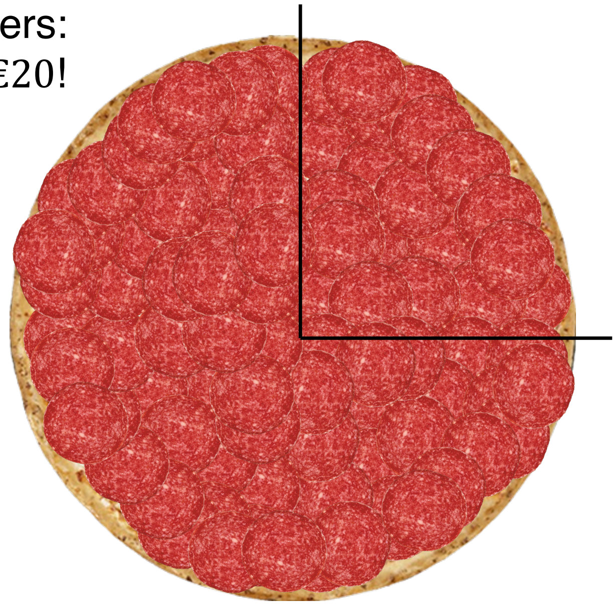
Overvaluation: illustration



Newspapers: a quarter of a pizza was sold for €5!
The pizza is worth €20!

Overvaluation: illustration

Newspapers:
$V_{pizza} = €20!$

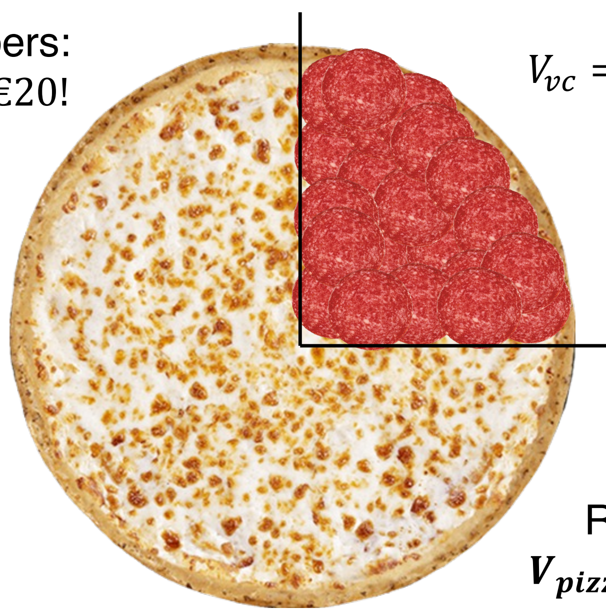


Newspapers report valuation as if the whole pizza is like VCs piece!

Overvaluation: everyone wins?

Newspapers:
$V_{pizza} = €20!$

$V_{vc} = €5$



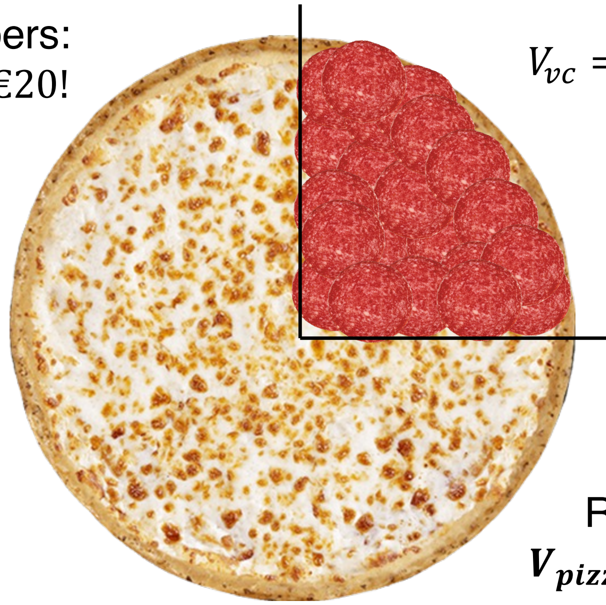
Reality:
$\boldsymbol{V_{pizza} = €10}!$

VCs are happy: they get a nice piece for €5

Overvaluation: everyone wins?

Newspapers:
$V_{pizza} = €20!$

$V_{vc} = €5$



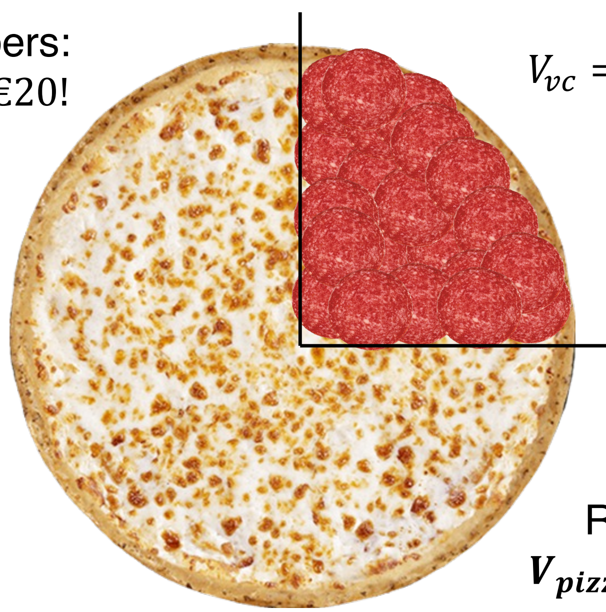
Reality:
$\boldsymbol{V_{pizza} = €10!}$

Founders are happy: startup was valued (by newspapers) at €20

Overvaluation: everyone wins?

Newspapers:
$V_{pizza} = €20!$

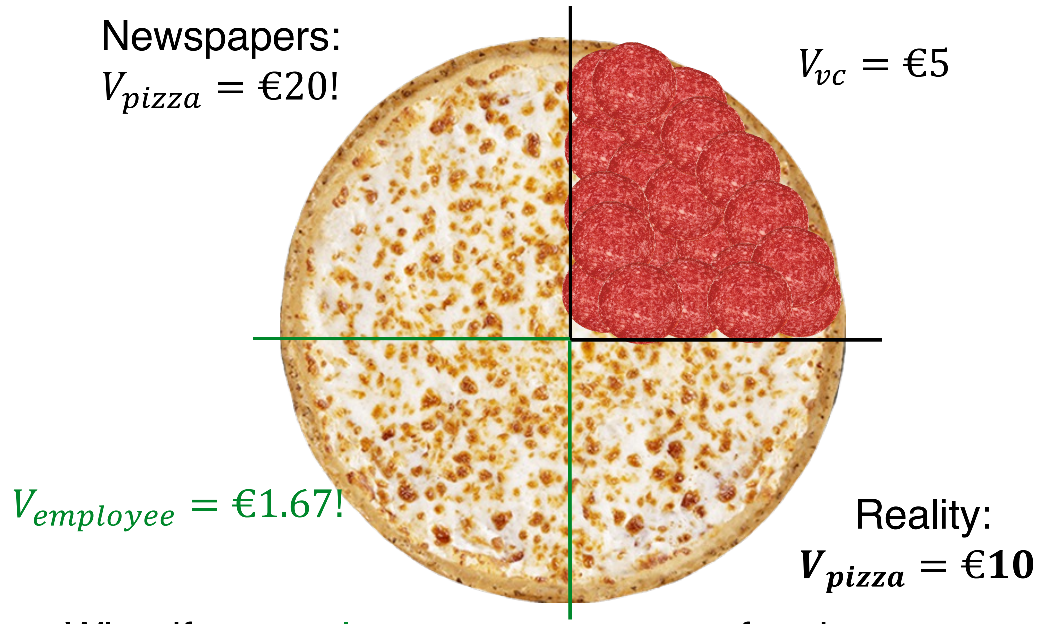
$V_{vc} = €5$



Reality:
$\boldsymbol{V_{pizza} = €10!}$

What about **employees?**
What if an employee gets a quarter of a pizza as part of compensation?

Overvaluation: everyone wins?

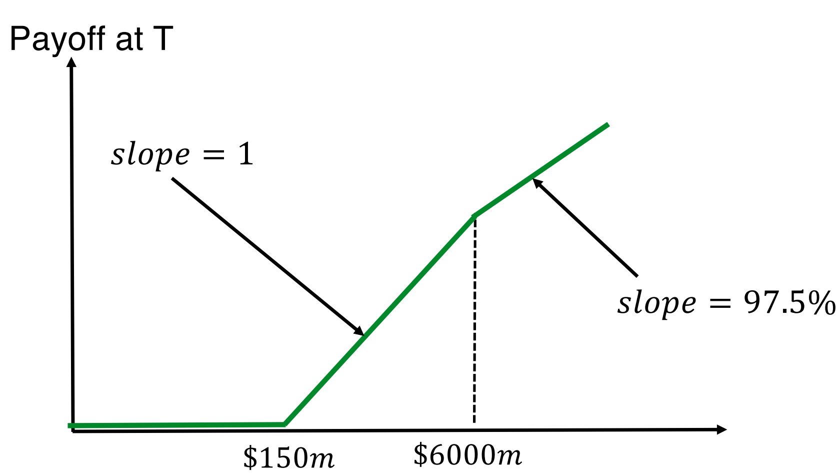


What if an employee gets a quarter of a pizza as part of compensation?

$$V_{employee} = \frac{1}{3}€5 = €1.67 < \frac{1}{4}€10 < \frac{1}{4}€20.$$

Square Case: common equity holders' payoff

$$\begin{aligned}
&\text{Payoff to common shareholders at exit} \\
&= V_T - \text{Payoff to Series E investors at exit} \\
&= V_T - (V_T - C_T(150, V_T) + 0.025 \cdot C_T(6000, V_T)) \\
&= C_T(150) - 0.025 \cdot C_T(6000)
\end{aligned}$$



Square Case: employee's story

Suppose you have accumulated 100,000 units of the company's common shares…

- You own a fraction $100k/378.3m$ of all common shares
- $\text{Value of all common shares} = \text{Total value} - \text{value of convertible preferreds} = \$2.356\text{bn} - \$150\text{m} = \$2.206\text{bn}$
- $\text{Value of your stake} = \frac{100k}{378.3m} \cdot \$2.206\text{bn} = \$583\text{k}$

Square Case: employee's story

Two ways **not** to proceed:

- You own a fraction $100k/(378.3\text{m} + 9.7\text{m})$ of **all shares**

1. $\text{Value of your stake} = \frac{100k}{378.3\text{m}+9.7\text{m}} \cdot \$6\text{bn} = \$1546\text{k}$
   - What's wrong: Square value is not $6bn
2. $\text{Value of your stake} = \frac{100k}{378.3\text{m}+9.7\text{m}} \cdot \$2.356bn = \$607\text{k}$
   - What's wrong: your shares are different from VCs'

Square Inc: beyond the case

Swiped
A profitless payment firm goes public

A private fundraising last year valued Square at roughly $6 billion. The initial public offering (IPO) priced it at $2.9 billion, down by half. The valuation sent a frisson through Silicon Valley…

The Economist, Nov 19, 2015.

- IPO valuation is actually higher than the true value in previous round!

Are unicorns overvalued?

Academic research (Strebulaev and Gornall, 2020) shows that:

- After adjusting for overvaluation (similarly to how we did it for Square Inc) **almost one-half (65 out of 135) of US unicorns lose their unicorn status.**

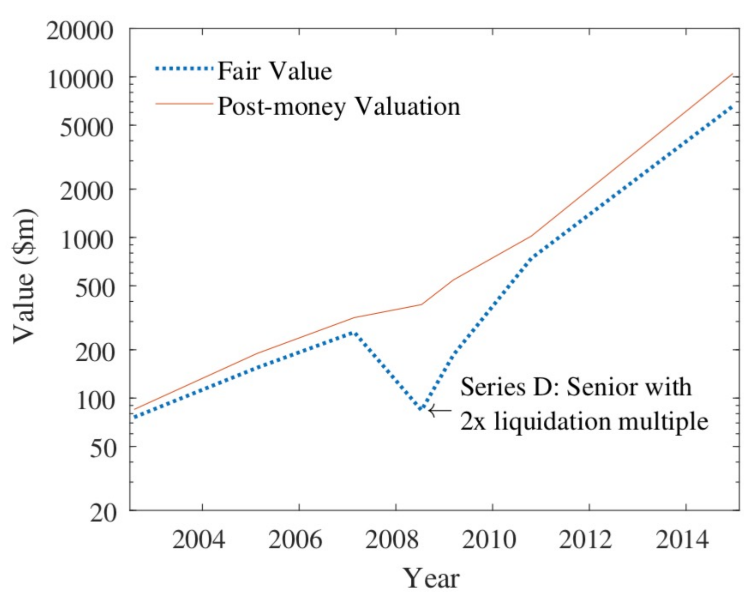
Are unicorns overvalued?

Academic research (Strebulaev and Gornall, 2020) shows that:

- After adjusting for overvaluation (similarly to how we did it for Square Inc) **almost one-half (65 out of 135) of US unicorns lose their unicorn status.**
- reported unicorn **post-money valuations average 48% above fair value**
- They calculate Square Inc fair value to be **$2.3bn**
    - Our valuation is close! (Even though we've made simplifying assumptions)

Are unicorns overvalued?

Space X series D example: true value falls by 67%, reported value increases by 36%.



Source: Strebulaev and Gornall, 2020

Summary

Unicorns are overvalued:

- As shown in academic research
- As seen in Square Inc case

Why?

- Reported valuations ignore option features embedded in the shares that VCs get

Outlook

Next class: capital structure.

F Session on IPOs

Session 12: IPOs

Corporate Financial Policy
INSEAD MBA Program
Professor Sergei Glebkin

Plan for today

IPOs

- IPO goals
- Pros and cons of going public
- IPO mechanics
- IPO underpricing

IPO goals

> **Bloomberg** **Dropbox, Valued Privately at $10 Billion, Files for U.S. IPO**
>
> The company filed with an offering size of $500 million…The company plans to use the proceeds to pay down debt and for general corporate purposes.

Bloomberg, Feb 23, 2018.

- Most common goal: to raise money

How much money did Dropbox actually raise?

- Dropbox issued $36m$ new shares
  - These new shares are called primary shares
- Offer price($\$21$) minus underwriting discount was $\$20.0655$.
- Money raised= $20.0655 \cdot 36 = \$722.358m$.

IPO goals

> **FT** FINANCIAL TIMES **Why Spotify is risking an unconventional IPO**
>
> Spotify is planning to float shares as early as this month…
>
> Spotify will not sell new shares… its early shareholders, including Mr Ek, co-founder Martin Lorentzon as well as hedge fund Tiger Global, can sell.

FT, Mar 12, 2018

- Since new shares won't be sold, Spotify is not raising money in this IPO
  - Which shares will be sold? Secondary.
- What is the goal of this IPO? Exit

IPO goals

IPO goals:

- Most common goal: to raise money.
- Spotify's case: provide VCs and other early shareholders with an exit.

Terminology:

- New shares sold at IPO: primary shares
- Existing shares, held by early shareholders: secondary shares

Pros and cons of going public

Advantages:

- Better access to capital
    - Public markets often give access to much larger amounts of capital

Dropbox equity financing:

Mar 23, 2018	IPO	$722m
Jan 24, 2014	Series C	$350M
Oct 18, 2011	Series B	$250M
Nov 24, 2008	Series A	$1.2M

Pros and cons of going public

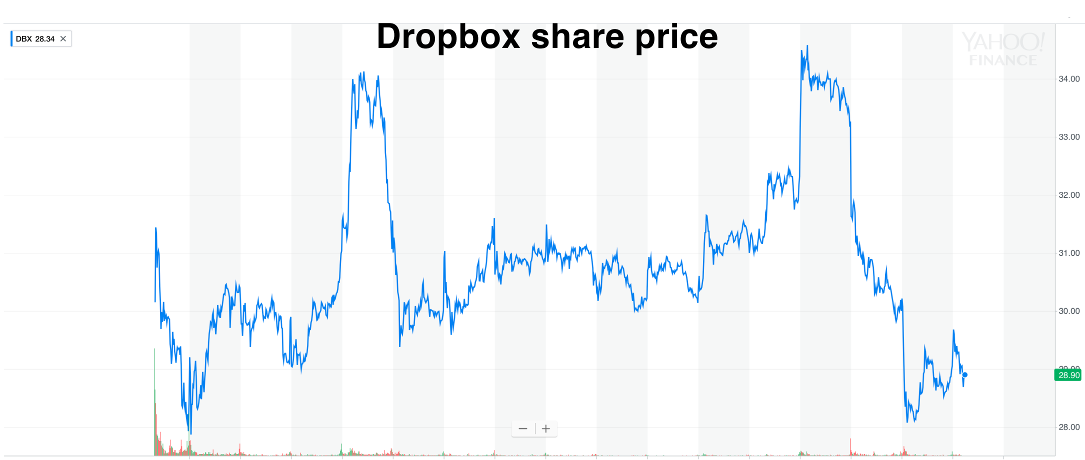
Advantages:

- Better access to capital
- Liquidity
    - If an investor wants to buy/sell shares of a company, can do so quickly and with low transaction costs

Pros and cons of going public

Advantages:

- Better access to capital
- Liquidity
- Real-time feedback from markets



Pros and cons of going public

Disadvantages:

- Lack of ownership concentration
  - When early shareholders diversify their holdings, ownership becomes more dispersed
  - A solution: issue shares with less voting power

WSJ

In Snap IPO, New Investors to Get Zero Votes, While Founders Keep Control

Evan Spiegel and Bobby Murphy… are expected to hold more than 70% of the voting power despite owning roughly 45% of the stock

WSJ, Jan 16, 2017.

Pros and cons of going public

Advantages:

- Better access to capital
- Liquidity
- Real-time feedback from markets

Disadvantages:

- Takeover threats
- Lack of ownership concentration
- Potential short-termism
- Public companies are more tightly regulated. Compliance can be costly.

Types of IPO

We will discuss three major types of IPOs

1. **Firm commitment** (underwritten)
2. Auction
3. Direct listing
4. ~~SPACs~~

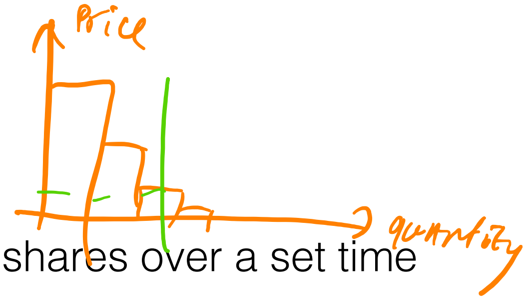
Types of IPO

Firm commitment IPO

- Underwriters buy the entire issue (at offer price minus underwriting discount) and sell it at an offer price
- Offer price is set by underwriters
- Example:

Snap Inc.

Types of IPO



Auction IPO

- Investors bid for company's shares over a set time
- The price is set automatically: highest price such that all shares are sold given investors' bids
- Example:

Google

Types of IPO

Direct listing

- The company directly makes its shares available for trading by public investors, no help from underwriters
- The starting price is determined by supply and demand in the public market
- Example:

Spotify®

Mechanics of an IPO: firm commitment

Most widely used mechanism

The process takes 6-12 months, following steps

Choice of underwriters → Registration → Road show → Book building → Offer price is Determined. Shares are allocated at offer price → Stock starts trading At the stock exchange

secondary market

primary market

Mechanics of an IPO: the case of Snap

Filed Pursuant to Rule 424(b)(4)
Registration No. 333-215866

PROSPECTUS

200,000,000 Shares

Snap Inc.

Class A Common Stock

This is an initial public offering of shares of non-voting Class A common stock of Snap Inc.

Snap Inc. is offering to sell 145,000,000 shares of Class A common stock in this offering. The selling stockholders identified in this prospectus are offering an additional 55,000,000 shares of Class A common stock. We will not receive any of the proceeds from the sale of the shares being sold by the selling stockholders.

Source: SNAP Final Prospectus

Issue size:

Primary shares:

Secondary shares:

Mechanics of an IPO: the case of Snap

UNDERWRITING

Under the terms and subject to the conditions in an underwriting agreement dated the date of this prospectus, the underwriters named below, for whom Morgan Stanley & Co. LLC and Goldman, Sachs & Co. are acting as representatives, have severally agreed to purchase, and we and the selling stockholders have agreed to sell to them, severally, the number of shares of our Class A common stock indicated below:

Underwriters	Number of Shares
Morgan Stanley & Co. LLC	60,484,615
Goldman, Sachs & Co.	49,600,000
J.P. Morgan Securities LLC	26,500,000
Deutsche Bank Securities Inc.	20,000,000
Barclays Capital Inc.	12,000,000
Credit Suisse Securities (USA) LLC	6,153,846
Allen & Company LLC	14,000,000
BTIG, LLC	923,077
C.L. King & Associates, Inc.	123,077
Citigroup Global Markets Inc.	1,230,769
Connaught (UK) Limited	307,692
Cowen and Company, LLC	923,077
Evercore Group, LLC	615,385
Jefferies LLC	615,385
JMP Securities LLC	307,692
LionTree Advisors LLC	923,077
LUMA Securities LLC	307,693
Mischler Financial Group, Inc.	123,077
Oppenheimer & Co. Inc.	615,385
RBC Capital Markets, LLC	1,230,769
Samuel A. Ramirez & Co., Inc.	123,077
Stifel Financial Corp.	923,077
SunTrust Robinson Humphrey, Inc.	307,692
The Williams Capital Group, L.P.	123,077
UBS Securities LLC	1,230,769
William Blair & Company, L.L.C.	307,692
Total	200,000,000

Source: SNAP Final Prospectus

Mechanics of an IPO: the case of Snap

	Price to Public	*Underwriting Discounts and Commissions (1)*	*Proceeds to Snap Inc.*	*Proceeds to Selling Stockholders*
Per share	*$17.00*	*$0.425*	*$16.575*	*$16.575*
Total	*$3,400,000,000.00*	*$85,000,000.00*	*$2,403,375,000.00*	*$911,625,000.00*

(1) See "Underwriting" for a description of the compensation payable to the underwriters.

At our request, the underwriters have reserved up to 7.0% of the shares of Class A common stock offered by this prospectus for sale, at the initial public offering price, to certain institutions as well as individuals associated with us. See "Underwriting—Directed Share Program."

To the extent that the underwriters sell more than 200,000,000 shares of Class A common stock, the underwriters have the option to purchase up to an additional 30,000,000 shares of Class A common stock from us and certain of the selling stockholders at the initial public offering price less the underwriting discount.

Source: SNAP Final Prospectus

Over-allotment allocation: 30m

Supports the price in the public market

- Issue size is 200m shares. Underwriters sell 230m shares to their clients. Where do they get additional 30m shares?
- If the issue is a success, i.e. price in the public market is high, (> 16.575) underwriters buy 30m additional shares from Snap (at $16.575)
- If the issue fails, i.e. price in the public market is low (< $16.575), underwriters buy 30m additional shares from public market, thereby supporting the price

Mechanics of an IPO: the case of Snap

	Price to Public	Underwriting Discounts and Commissions(1)	Proceeds to Snap Inc.	Proceeds to Selling Stockholders
Per share	$17.00	$0.425	$16.575	$16.575
Total	$3,400,000,000.00	$85,000,000.00	$2,403,375,000.00	$911,625,000.00

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To the extent that the underwriters sell more than 200,000,000 shares of Class A common stock, the underwriters have the option to purchase up to an additional 30,000,000 shares of Class A common stock from us and certain of the selling stockholders at the initial public offering price less the underwriting discount.

Source: SNAP Final Prospectus

Underwriter buy one share from Snap at $__ and sell to their clients at $__

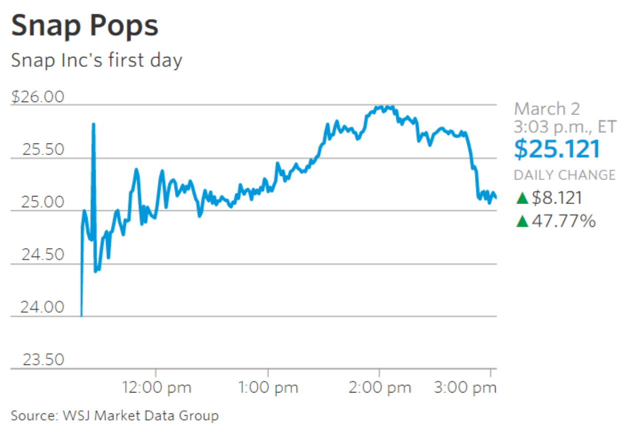
Total fees of underwriters: $0.425 × 230m = $97.75m

WSJ **Spotify's Splashy Debut Pressures Banks**

Spotify... paid… about $36 million in total fees. Snap, which was similar in size during its March 2017 offering, paid nearly $100 million.

WSJ, Apr 3, 2017.

Mechanics of an IPO: the case of Snap



- Offer price: $17
- First day closing price: $24.48
- IPO was underpriced

IPO underpricing

SNAP: Offer price=$17. First day close=$24.48

Winners

- Underwriters' clients: bought at $17 and can sell at the end of the first day at $24.48

Losers

- Snap: could raise $24.48/share but only raised $17

Money left on the table

$= (\text{First day close} - \text{Offer price}) \cdot \#\text{ of shares offered}$

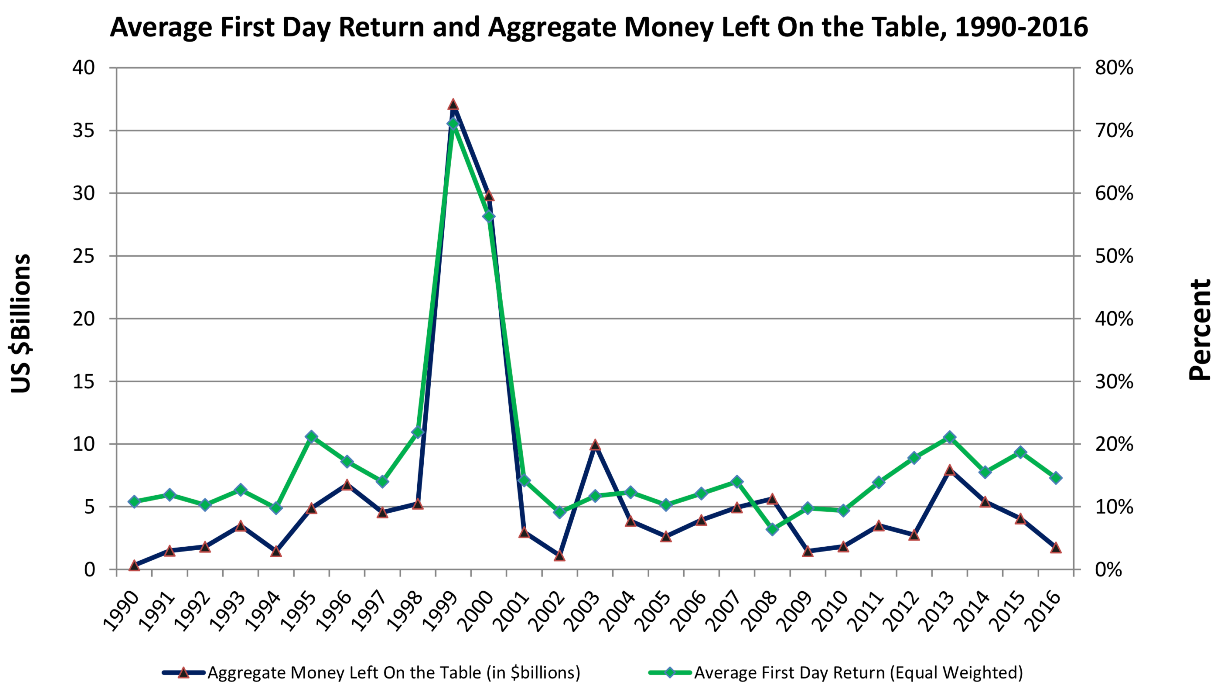
$= (\$24.48 - \$17) \cdot 200m = \$\mathbf{1.496}\boldsymbol{bn}!$

IPO underpricing

Some big IPOs for money left on the table

Company	IPO date	$ left on the table
VISA	Mar 19, 2008	$5.075bn
ups	Nov 10, 1999	$1.597bn
	Nov 7, 2013	$1.323bn

IPO underpricing



Source: Jay Ritter, IPO Updated Statistics

IPO underpricing: explanations

1. Popular answer: banker greed

- Underpriced IPOs that have a huge pop on the first day are a hot currency that bankers use to trade favors with their favorite customers

> **The New York Times** — **Was LinkedIn Scammed?**
>
> The first-day gain was close to 110 percent...
>
> ...hundreds of millions of additional dollars that should have gone to LinkedIn wound up in the hands of investors that Morgan Stanley and Merrill Lynch wanted to do favors for.

NYT op-ed, May 20, 2011

- Why not eliminated by competition?

IPO underpricing: explanations

2. Winner's curse

ABC, Inc., is going public with $10 offer price. With 80% chance the IPO is going to be hot: first day return=20%. With 20% chance the IPO is going to be cold: first day return=-8%. You want to buy 100 shares at IPO and sell them at the end the day. You understand that in hot IPO you'll only get 1/10 of your bid due to oversubscription. In cold IPO you'll get all 100 shares. Calculate your expected profit.

- Money you make in hot market 80% $\frac{1}{10} 100\,(20\%)\,\$10 = \$20$
- Money you make in cold market −20% $100(-8\%)\,\$10 = -\$80$
- Expected profit, expected return $0.8 \cdot \$20 + 0.2(-\$80) = 0$
- Naïve calculation: $\text{expected return} = 0.8 \cdot 20\% - 0.2 \cdot 8\% = 14.4\%$

IPO underpricing: explanations

2. Winner's curse

- Getting all shares you wanted to buy in IPO is bad news: IPO is cold

"I wouldn't want to belong to a club that would have me as a member"

— Groucho Marx

- To entice people to participate in the market, bankers need to underprice the shares, so that on average there is some gain for them

Pros and cons of going public

Advantages:

- Better access to capital
- Liquidity
- Real-time feedback from markets

Disadvantages:

- Takeover threats
- Lack of ownership concentration
- Potential short-termism
- Public companies are more tightly regulated. Compliance can be costly.

Summary

IPOs

Advantages:

- Better access to capital
- Liquidity
- Real-time feedback from markets

Disadvantages:

- Takeover threats
- Lack of ownership concentration
- Potential short-termism
- Public companies are more tightly regulated. Compliance can be costly
- Underpricing, likely compensates participating investors for winner's curse

Outlook

Next class: The case of Hertz

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