Essays on Amplification Mechanisms in Financial Markets

by

Marco Di Maggio

Submitted to the Department of Economics
in Partial Fulfillment of the Requirements for the Degree of
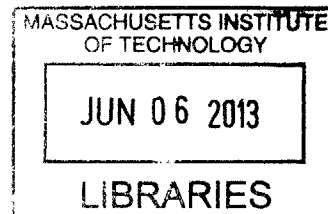
Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2013

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Abstract

In Chapter 1, I explore how speculators can destabilize financial markets by amplifying negative shocks in periods of market turmoil, and confirm the main predictions of the theoretical analysis using data on money market funds (MMFs). I propose a dynamic trading model with two types of investors – long-term and speculative – who interact in a market with search frictions. During periods of turmoil created by an *uncertainty shock*, speculators react to declining asset prices by liquidating their holdings in hopes of buying them back later at a gain, despite the asset's cash flows remaining the same throughout. Interestingly, I show that a reduction in trading frictions leads to more severe fluctuations in asset prices. At the root of this result are the strategic complementarities between speculators expected to follow similar strategies in the future. Using a novel dataset on MMFs' portfolio holdings during the European debt crisis, I gauge the strength of funds' strategic interactions as the number of funding relationships each issuer has with MMFs. I show that funds are more likely to liquidate the securities of issuers that have fewer funding relationships with other funds, obliging them to borrow at shorter maturity and higher interest rates.

In Chapter 2, co-authored with Marco Pagano, I study a model where some investors ("hedgers") are bad at information processing, while others ("speculators") have superior information-processing ability and trade purely to exploit it. The disclosure of financial information induces a trade externality: if speculators refrain from trading, hedgers do the same, depressing the asset price. Market transparency reinforces this mechanism, by making speculators' trades more visible to hedgers. As a consequence, asset sellers will oppose both the disclosure of fundamentals and trading transparency. This is socially inefficient if a large fraction of market participants are speculators and hedgers have low processing costs. But in these circumstances, forbidding hedgers' access to the market may dominate mandatory disclosure.

In Chapter 3, I show that reputation concerns are important sources of discipline for institutional investors, but their effectiveness varies along the business cycle. I propose a dynamic model of reputation formation in which investors learn about fund managers' skill upon observing past returns. Managers can generate active returns at a disutility and determine the fund's exposure to tail risk. The model delivers rich dynamics for managers' behavior. Good reputation managers exploit their status by extracting higher rents from investors, while intermediate reputation managers tend to improve their returns to attract more funds. Finally, for bad performers there exists a *reputation trap*: their perceived low quality prevents them from attracting investors' capital and then also from improving their track record. Furthermore,

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when the economy is subject to aggregate shocks, fund managers tend to exacerbate fluctuations by exposing the fund to tail risk to increase short-term returns. The model provides a framework to analyze the investment strategies adopted by mutual funds and hedge funds during the recent financial crisis.

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Acknowledgments

In completing this dissertation, I benefited from the generous help of many individuals. First and foremost, I am extremely grateful to my advisors Daron Acemoglu, Abhijit Banerjee, Stephen A. Ross and Andrey Malenko.

Professor Acemoglu, whose work has been a deep source of personal inspiration, offered invaluable guidance and support during the entire process. His breadth of knowledge, from history to politics, from sociology to mathematics, together with his infinite generosity with time, makes him a terrific advisor. I still remember when during the visiting days he accepted to be my advisor. I am indebted with him for keeping his word. I am grateful to him for always holding me to a higher standard and for teaching me the importance of form and exposition in research. During these five years, he was able to understand the right moment to shake me and when I truly needed a hug.

Professor Banerjee's sharp and deep insights were extremely important for my work. He was able to find the promising angle in my vague ideas and help me transform them in this dissertation. I am indebted with him for making me feel at ease when going to his office and engage in fruitful conversations about my projects, which invariably resulted in a more robust understanding of my own work. Working on a joint project with him is for me one of the highest achievements of these years. But, above all, I am especially grateful to him for believing in me at a time in which I was in great need of that.

Professor Ross taught me that to become a better financial economist I should spend more time investigating the real world rather than reading the existing research papers. I am honored to be one of his students, and he made me feel part of an elite. Moreover, his simplicity and availability made it possible to build a precious personal relationship between us. I am especially thankful for his ability to keep track of my progress, even at times when he was very busy or out of town. His numerous calls during my job search were essential to overcome the tough times. For making me one of his priorities I will be forever grateful.

Professor Malenko was extremely helpful during my last two years at MIT. His guidance and advice were essential in the development of the first and third chapter of this dissertation. He encouraged me since our first meeting and his willingness to answer all of my questions and doubts about the job market process was essential. I also thank him for his remarkable

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of remaining unemployed. The possibility to see now the pride in her eyes and the enthusiasm of beginning a new chapter of our lives together, makes me believe that it was all worth it. She has witnessed the evolution of this thesis from the very first draft to completion and her love and support took much of the heavy load off my shoulders and brought balance into my life. She was willing to risk it all by leaving Italy to stay with me. For being so brave and for helping me to become a better man, I will never thank her enough.

Marco Di Maggio

Cambridge, Massachusetts

To Roberta, the love of my life

Chapter 1

Market Turmoil and Destabilizing Speculation

1.1 Introduction

Uncertainty has dominated financial markets of late. The most striking example is the sovereign debt crisis in Europe, but as the market volatility index (VIX) shows, US financial markets experienced similar periods of high uncertainty in the periods surrounding the failure of Lehman Brothers, in the aftermath of 9/11, and following the default of Long-Term Capital Management in 1998 (Figure 1-1). Uncertainty has been held to be a key drag on the recovery from the recession of 2007-2009, and a burgeoning literature considers possible mechanisms.[1] One negative effect of uncertainty working through financial channels has been studied by Ellul et al. (2012), who consider several episodes of market turmoil dating back to the 1987 market crash and show that speculators amplify the effects of negative market-wide shocks by demanding liquidity at times when other potential buyers' capital is scarce.[2] This suggests that certain

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[1] Reasons for an uncertainty drag include lower incentives to invest (Bernanke (1983) and Bloom (2009)) higher costs of capital for firms (see for instance Gilchrist et al. (2010) and Fernandez-Villaverde et al. (2011)), increasing managerial risk aversion (Cochrane (2011) and Panousi and Papanikolaou (2012)), increasing risk premium (Pastor and Veronesi (2011a)) and an intensification of agency problems (Narita (2011)).

[2] To define periods of "market turmoil," Ellul et al. (2012) use both the S&P500 Index and the VIX over the period 1986-2009. They focus on quarters during which there is a month when the S&P500 returns fall below the 5th percentile and the VIX changes are above the 95th percentile. This procedure identifies three quarters: the fourth quarter of 1987, the third quarter of 1998, and the third quarter of 2008.

investors' behavior in times of high uncertainty determines how severe the effects of negative shocks and their propagation will be.

In this paper, I theoretically explore the role of speculators during periods of market turmoil and show that, as hinted at by Ellul et al. (2012), instead of stabilizing financial markets, speculators amplify price fluctuations by selling their holdings. I propose a continuous-time model with two types of investors – long-term and speculative – in a market with trading frictions. Long-term investors offer a downward-sloping demand curve to other market participants, whereas speculators trade off the cash flow from holding the asset against the expected capital gains from aggressively exploiting temporary deviations of the price from the long-term value of the asset. A key element in the analysis is the introduction of uncertainty shocks, defined as the possibility that at some random time in the future the market will be subject to a negative shock with a small but positive probability. I model these shocks as an increase in supply, which makes the price deviate temporarily from its fundamental value. The initial shock that makes speculators aware of this possibility can be interpreted as an "uncertainty shock" (Bloom (2009)) or an "anxiety shock" (Fostel et al. (2010)), as it increases the uncertainty in the economy. The adverse shocks, which create price pressure, capture the possibility that regulatory constraints, or margin requirements may force other investors to sell in the future.

The model reveals a novel mechanism whereby some investors could aggravate market shocks: during high-uncertainty periods, speculators react to declining prices by liquidating their holdings because they expect further turmoil. This generates *endogenous volatility* by further depressing prices, and leads to price reversals once the shock occurs. Speculators trade off the cash flow from holding against the expected capital gain from selling and buying back the asset when the market bottoms out. The size of the capital gains depends crucially on the behavior of the other speculators who trade in the future. In fact, strategic interactions among speculators are at the root of the amplification of non-fundamental shocks during periods of high uncertainty, and their importance for money market funds (MMFs) is investigated empirically.

The first finding is that two different equilibria can arise: a *"leaning-against-the-wind"* equilibrium and a *"cashing-in-on-the-crash"* equilibrium. In the former, speculators react to the uncertainty shock by buying, because they expect the speculators who trade in the future to buy

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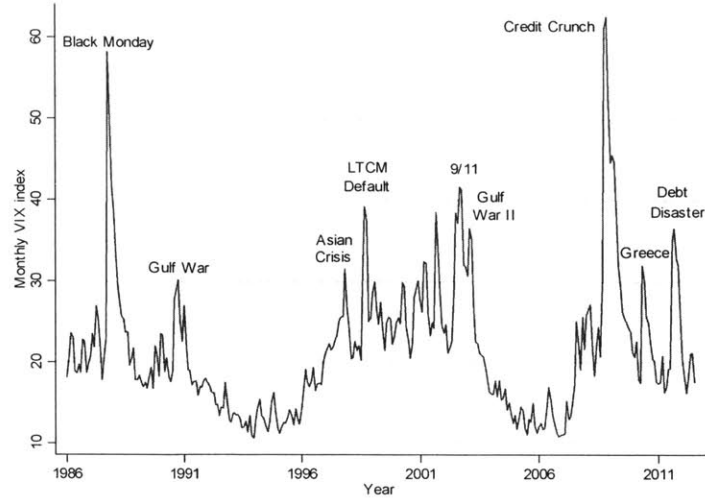
Figure 1-1: Monthly U.S. stock market implied volatility. Notes: Chicago Board Options Exchange VXO index of percentage implied volatility, on a hypothetical at-the-money S&P500 option 30 days to expiration, from 1986 onward. A new methodology was introduced on September 22, 2003. See the CBOE website for a description of the key enhancements to the VIX methodology.

as well, which leads to an increase in the price. Thus, in this equilibrium investors stabilize the market by absorbing the excess supply, as predicted by the standard arbitrage theory (Friedman (1953)). In the "cashing-in-on-the-crash" equilibrium, however, the speculators behave differently. Because they expect a further price fall due to the potential realization of a shock and, more importantly, due to endogenous price movement driven by the price impact of speculators trading in the future, they start selling until the uncertainty is resolved by the occurrence of the shock. Thus, speculators depress the price *in anticipation* of a negative shock, and to a greater extent than would be the case in the absence of speculators. In this equilibrium the speculators destabilize the market even when the asset's long value is unaffected, as speculators could continue to hold the asset and capture its cash flow. Interestingly, less trading friction is associated with sharper price decline and faster recovery once the shock hits.

To determine under what conditions such destabilizing trading is most likely to emerge, I investigate the market characteristics that affect investors' incentives and influence which equilibrium emerges. I derive three main predictions. First, when uncertainty is short-lived speculators have a greater incentive to liquidate before the shock, as the period during which

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they have to forgo the asset's cash flow is shorter. Second, it is more likely that speculators will amplify fluctuations in relatively illiquid markets. And third, trading friction has a non-monotonic effect on speculators' incentives, because it plays two opposing roles: on the one hand, it determines the speed with which speculators can trade and exploit price movements, and on the other it determines the size of the price movement before the shock. The relative absence of trading friction always increases the incentive to profit from the capital gain, because speculators can sell the asset when the price is high, expecting to buy it back immediately after the shock, when the price is lower. But even with significant trading friction speculators have an incentive to trade in the direction of the shock, because the expected price movement until the next trading opportunity is limited. By contrast, for intermediate levels of trading friction, speculators find it optimal to buy and hold to capture dividends, as the expected capital gain from trading is small.

To gain further insight, I relax the assumption that the severity of the future shock is known and constant, positing instead that it follows a Brownian motion that is commonly observed by market participants. This scenario captures the idea that speculators know that a shock may come in the future, but that the situation may either improve or deteriorate over time. In addition to capturing an interesting feature of reality, this extension has the advantage of generating a unique equilibrium: speculators sell if the expected shock is larger than a (unique) threshold, and buy when it is smaller.

Three key properties follow from this characterization. First, this equilibrium shows that a small perturbation to speculators' perception of the severity of the future shock can have discontinuous effects, leading them to liquidate their holdings abruptly and further depress prices. That is, markets become *fragile*. Second, this threshold is decreasing in price, which suggests that in bull markets the expectation of a small future shock is sufficient to generate a sudden wave of selling, causing a price crash. Third, when the severity of the shock is above the threshold magnitude, the price decreases over time, and when it is below it the price rises towards the fundamental value.

Using a novel dataset of the monthly portfolio holdings of MMFs during the European debt crisis, I provide suggestive evidence for these theoretical results based on a "quasi-experiment." I analyze the response of MMFs to the spike in uncertainty caused by the crisis that erupted

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in October 2011. To gather evidence for the model's main mechanism, namely, strategic interaction among speculators, I exploit cross-sectional variation across financial institutions and corporations that meet their short-term borrowing needs in money markets. In the model, the size of the capital gains increases if other speculators are expected to follow similar strategies in the future, which suggests a substantial role for complementarity in amplifying negative shocks. The strength of the strategic interactions among funds is measured as the number of funding relationships each issuer has with other funds. Issuers that sell their commercial paper to or have repurchase agreements with fewer funds in the period before the uncertainty shock should be more vulnerable to the funds' trading strategies, because funds should focus their cashing-in-on-the-crash trading on those assets for which they have a larger impact.

In line with the predictions of the model, I show that funds are much more likely to liquidate the assets of issuers that have fewer funding relationships with other funds. A one-standard-deviation decrease in the number of relationships reduces the funds' exposure to these issuers by at least 0.3 percent of assets under management, which constitutes 63 percent of the cross-sectional variation in the mean outcome. To take account of the possible differences across institutions that have a different number of funding relationships, I include issuer-fixed effects in all of the specifications. Another concern is that the rise in uncertainty in October 2011 increased the riskiness of issuers with fewer funding relationships, inducing the funds to liquidate the securities of these issuers. However, I show that the estimates are robust to the inclusion of issuers' credit default swap premia. These results show that price destabilization is greater for the assets characterized by greater complementarity among funds and that it is not driven by precautionary motives stemming from a higher level of risk. I also investigate several alternative explanations based on funds' fear to "break the buck" in the near future, on their desire to diversify their portfolio across regions of risk and on potential unobserved changes, after October 2011, in the liquidity of the different assets.

Some analysts have argued that "European banks [were] seeing their funding and U.S. dollar liquidity position squeezed, forcing them to pay higher fees and putting further pressure on earnings and on capital positions."[3] To analyze the effects of funds' trading strategies on European financial institutions, I look at how the maturity and yields of the assets issued

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[3] "More Trouble For Euro Banks: Money Market Funds Cut Exposure By 37%", *Forbes*, 21 October, 2011.

by different institutions are affected, finding that issuers with few funding relationships were affected more strongly than those with more relationships, obliging them to borrow at shorter maturity and higher interest rates. This finding supports the prediction of the model: strategic trading by money market funds may intensify the effect of shocks, particularly when their trades have a greater impact on the market.

This consideration informs regulators' concerns about the fragility of the European financial system. In the words of the European Systemic Risk Board: "High uncertainty and associated fragility persist in the EU financial system and markets remain vulnerable".[4] This vulnerability is partly explained by institutions' reliance on money market funds for short-term funding, and by the funds' incentives to profit from periods of higher uncertainty.

The paper is organized as follows. The remainder of this section discusses the related literature. Section 2.3 presents the baseline model and Section 1.3 characterizes the two equilibria that can arise and the resulting price paths. Section 1.3.3 analyzes the impact of trading frictions, market liquidity and the persistence of uncertainty on equilibrium behavior. Section 1.3.4 extends the model to study the effect of the introduction of a transaction cost such as a Tobin tax. Section 1.3.5 presents my uniqueness result and the result on market fragility. Section 1.4 gives evidence for the main mechanism hypothesized and Section 1.5 weighs the different motivations underlying funds' strategies. Section 1.6 provides further insights on funds' trading behavior during the European debt crisis by exploiting cross-sectional variation across funds. Section 1.7 presents additional empirical predictions. Finally, Section 1.8 discusses the findings and concludes. The appendix contains the proofs.

1.1.1 Related Literature

This paper is related to several strands of literature. Fundamentally, it is part of the search literature following Duffie et al. (2005), and Duffie et al. (2007), which treats liquidity shocks (as captured by a shift in the preferences of all market participants in the spirit of Grossman and Miller (1988)) in secondary markets with trading frictions. The most closely related papers are Weill (2007) and Lagos et al. (2011), which consider out-of-steady-state dynamics and dealers' liquidity provision when dealers can hold inventories *in response to* an aggregate liquidity shock

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[4] This press release by the ESRB is available at http://www.esrb.europa.eu/news/pr/2012/html/pr120920.en.html.

of the same type as in Duffie et al. (2007).[5] The distinctive feature of my analysis is the focus on investors' trading strategies *in anticipation* of a random negative shock, rather than on the dealers' responses. My first set of results yields new insight into how the interaction between speculators and long-term investors, and the resulting trading dynamics, might accentuate negative shocks by depressing the price even beyond the real effect of the shock.[6]

Several recent studies analyze the role of uncertainty shocks in macroeconomic models as well as in asset pricing models. Baker et al. (2011) propose a new index of policy-related economic uncertainty and estimate its dynamic relationship to output, investment, and employment. Pastor and Veronesi (2011a) show that political uncertainty reduces the value of the implicit put protection provided by the government to the market and also makes stocks more volatile and more closely correlated, especially when the economy is weak. In a similar framework, Pastor and Veronesi (2011a) show that uncertainty over the consequences of new policies explains why stock prices usually fall at the announcement of a policy change. My paper shares this literature's interest in uncertainty in financial markets, but I take uncertainty as exogenous and instead investigate in detail investors' behavior when uncertainty increases. In my model, the effects of uncertainty in heightening price volatility are amplified by the behavior of speculators in distressed markets. I contribute to this literature by empirically estimating the importance of investors' responses to uncertainty shocks, examining money market funds' behavior during the recent European sovereign debt crisis.[7]

This paper also enriches the literature on financial market runs and feedback effects. Bernardo and Welch (2004) study how dealers provide liquidity during a market run in a model in the tradition of Diamond and Dybvig (1983). Morris and Shin (2004) analyze a model in which

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[5] A related literature employs the techniques developed in the search literature on over-the-counter markets for theoretical analysis of the impact of high-frequency trading. For instance, Pagnotta (2010) shows that traders find it optimal to play a twofold role in the decentralized market, at once demanding and supplying liquidity, whereas Biais et al. (2011) and Jovanovic and Menkveld (2010) show that algorithmic traders –by processing information on stock values faster than other slower traders– generate adverse selection.

[6] Liquidity provision in normal times has been analyzed in traditional inventory-based models of market-making (see Chapter 2 of O'Hara (1995) for a review).

[7] Two additional amplification mechanisms have been shown to be important. First, Kiyotaki and Moore (1997) have highlighted agents' balance sheets, which might make them liquidate assets in response to a negative shock, driving prices down and thus further undermining their balance sheets, leading to the amplification of the initial shock. Second, investors' Knightian uncertainty about asset values might cause them to disengage from markets and in this way amplify the crisis (see Routledge and Zin (2009), Caballero and Krishnamurthy (2008), and Easley and O'Hara (2010)). The mechanism posited here complements these papers by specifying why and how markets become more fragile when uncertainty spikes.

traders with short horizons and loss limits interact in a market with long-horizon traders. He and Xiong (2012) analyze dynamic debt runs in a continuous-time model in which creditors must decide whether to roll over their loans to a bank at discrete points in time and, unlike standard models of runs, derive a unique equilibrium. The focus on the timing of arbitrage trades connects my work to Abreu and Brunnermeier (2002) and Abreu and Brunnermeier (2003). These authors analyze a model in which the emergence of a gap between the price and the fundamental value of an asset is exogenously given and informational asymmetries cause a problem of coordination over the optimal time to exit the market. In my model instead, information is symmetric, the price is endogenous, and the focus is on speculators' responses to an increase in uncertainty. Unlike these papers, my model assumes that what generates complementarities among speculators is an uncertainty shock, which exacerbates negative shocks by increasing endogenous volatility. I also estimate the impact of speculators' behavior on issuers' balance sheets, showing that issuers are forced to borrow at higher rates and shorter maturities.[8]

Finally, my paper is part of a large literature that has identified factors that limit arbitrageurs' ability to prevent mispricing: noise-trading risk (De Long et al. (1990)), fundamental risk (Campbell and Kyle (1993)), principal-agent problems (Shleifer and Vishny (1997)), coordination risk (Liu and Mello (2011), Carlin et al. (2007)), information barriers (Bolton et al. (2011b)), slow-moving capital (Mitchell et al. (2007), Duffie (2010) and Duffie and Strulovici (2011)), and wealth effects (Xiong (2001), Kyle and Xiong (2001), Gromb and Vayanos (2002), and Kondor (2009)). Compared with earlier research, I posit a different source of the limits to arbitrage – namely uncertainty about future market shocks in conjunction with trading frictions. The paper complements the literature by providing a new set of empirical predictions, which I test in Section 1.4.

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[8] A recent paper by Chen et al. (2010) analyzes mutual fund data and provides evidence that fragility in financial markets can be explained by strategic complementarities among investors. In particular, funds with illiquid assets (where complementarities are stronger) exhibit stronger sensitivity of outflows to bad past performance than funds with liquid assets.

1.2 Model

Overview. I propose a continuous-time model in which two types of investor, long-term investors and speculators, participate in a market characterized by trading frictions. That is, speculators cannot change their holdings continuously but only at discrete points in time. By holding the asset proportionally to the spread between price and fundamental value, long-term investors provide a downward-sloping demand curve to other market participants. Speculators, by contrast, trade off the cash flow from the asset in hopes of aggressively exploiting temporary deviations from the long-term value. One can interpret these speculators as sophisticated institutional investors, say hedge funds, that have the skills and the capital to provide liquidity in case of negative shocks that drive the price away from fundamentals. The key element of my analysis is the introduction of an uncertainty shock: the possibility that at some random future time the market will be subject to a negative shock with small, but positive, probability. I model this shock as an increase in asset supply, which causes the price to deviate from the fundamental value. My model aims to capture the speculators' behavior during market turmoil and their role in the destabilization of financial markets.

Environment. Time is continuous, runs forever and is indexed by $t \geq 0$. There is one asset and one perishable good, used as a numéraire. The asset is durable and in supply $S(t) > 0$, and its price is denoted by $p(t)$. The asset generates a constant cash flow stream, i.e. δdt over the interval $[t, t + dt]$. The numéraire good is produced and consumed by all agents. The instantaneous utility function of a speculator is $\delta a + c$, where a represents the asset's holdings, and $c \in \mathbb{R}$ is the net consumption of the numéraire good ($c < 0$ if the speculator produces more than he consumes). There are two types of infinitely-lived and risk-neutral agents who discount at the same rate $r > 0$: long-term investors and a unit mass of speculators. The analysis focuses on the decisions of the speculators. The drawback to assuming risk-neutrality consists in the possibility that it may be optimal for speculators to submit orders of infinite size. To preclude this, I assume that each speculator can hold at most one unit of the asset and cannot sell short, i.e. $a \in [0, 1]$.[9] Because agents have linear utility, considering only equilibria in which, at any

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[9]Such limits to the positions of arbitrageurs have been rationalized in the literature in a variety of ways, including risk aversion, wealth constraints and asymmetric information. Duffie et al. (2007) show that a risk-neutral investor acts more or less like a risk-averse investor in a search framework. The short-sales constraint

given time, a speculator holds either 0 or 1 unit of the asset does not undermine generality.

Trading Arrangements. A speculator can trade at random times T_α, distributed according to a Poisson distribution with intensity $\alpha > 0$. The processes are independent across speculators, which means that a fraction αdt of speculators get a chance to trade between t and $t + dt$. This friction has several interpretations.[10] First, it captures the frequency with which traders can submit orders. The importance of this delay, which is sometimes measured in milliseconds, is shown by the significant investments made by banks and other institutional investors to co-locate their servers next to those of the exchanges' themselves.[11] Second, it captures the time it takes for a hedge fund to structure a large deal with prime brokers or to consult and re-contract with clients.[12] Third, it might capture settings in which market monitoring is imperfect and costly so that agents are not always trading as in Biais and Weill (2009). In the context of the MMFs, these frictions might also capture regulatory constraints imposed on funds in terms of diversification and liquidity. I abstract from all other frictions, such as investors' fees to intermediaries, as considering them would not affect my results and would not add anything to the insights provided on this by Lagos and Rocheteau (2009).[13]

Apart from the speculators, the market consists of long-term investors. At each instant t a new unit mass of long-term investors enters the market and has a single opportunity to purchase the asset and hold it to maturity. These traders are price-takers and at each point in time they provide an aggregate demand of

$$D\left(p\left(t\right)\right) = \frac{1}{\lambda}\left(\frac{\delta}{r} - p\left(t\right)\right),\qquad(1.1)$$

depending on current price $p\left(t\right)$, the market depth λ, and the asset's expected discounted future

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can be relaxed, without affecting the main qualitative results, but at the expense of increasing the number of state variables, as well as tractability.

[10] The introduction of small trading frictions also overcomes the technical modeling problems associated with the sequencing of trades when time is continuous. For instance, I want to rule out non-measurable trading strategies, or strategies such as remaining in the market as long as possible, but exiting strictly by some given date t^*. Also, by imposing the assumption that trading opportunities arrive with Poisson rate α, we preclude clustering of trades.

[11] See for example the article "High-Frequency Trading Grows, Shrouded in Secrecy" available at http://www.time.com/time/business/article/0,8599,1914724,00.html .

[12] The explicit introduction of dealers into the model would not affect the analysis.

[13] As is shown by Lagos and Rocheteau (2009), the dealers' fees only reduce the rate at which orders arrive from α to $(1 - \eta)\alpha$ where η is the dealer's bargaining power. Instead, in section 1.3.4, I investigate the introduction of small trading costs, such as a "Tobin tax" on financial transactions.

cash flows $\frac{\delta}{r}$.

A larger λ means a steeper demand curve, i.e. lower liquidity by long-term investors. The demand curve (1.1) is proportional to the spread between the fundamental value $\frac{\delta}{r}$ and the actual price $p(t)$. Graham (2003) calls this spread a safety margin. It represents the net present value of profits to long-term investors when they hold the assets forever and collect the entire future cash flow.[14]

The long-term investors' demand schedule (1.1) is based on two assumptions. First, it is downward-sloping, since in order to hold more of the risky asset, traders must be rewarded with a lower price. This could be due either to risk aversion or to institutional frictions that make the risky asset less attractive for long-term investors than for speculators.[15]

The second assumption underlying (1.1) is that long-term investors' demand depends only on the current price $p(t)$. This follows from the assumption that they purchase the asset to hold it to maturity and have only a single opportunity to trade. In other words, they do not attempt to profit from price swings. Such conduct on the part of unsophisticated investors could also follow from the assumption that they lack the information, skills, or time to predict short-term price changes. In particular, my distinction between unsophisticated long-term investors and speculators could be interpreted as a distinction between traders who have the technology to trade at high frequency and take advantage of short-term price fluctuations, such as trading desks at investment banks and hedge funds, and investors such as mutual funds and pension funds, that tend to hold assets to maturity.[16]

The trading mechanism works as follows. The market clearing price $p(t)$ solves $D(p_t) + x(t) = S(t)$, where $x(t)$ is the fraction of speculators holding the asset at time t. Market clearing and equation (1.1) imply that the price is

$$p(t) = \frac{\delta}{r} - \lambda(S(t) - x(t)).\qquad(1.2)$$

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[14] Xiong (2001), Kyle and Xiong (2001) and Brunnermeier and Pedersen (2005), among others, employ a similar formulation for long-term investors' demand.

[15] A downward-sloping demand curve also arises in a price pressure model à la Grossman and Miller (1988) since the competitive but risk-averse market-making sector is only willing to absorb the selling pressure at a lower price. Alternatively, if speculators have private information about the fundamental value v, then the long-term investors face an adverse selection problem that naturally leads to a downward-sloping demand curve as in Kyle (1985).

[16] Notice that while the downward-sloping property of the residual demand function and its dependence only on the current price $p(t)$ are essential to my analysis, the specific functional form is not.
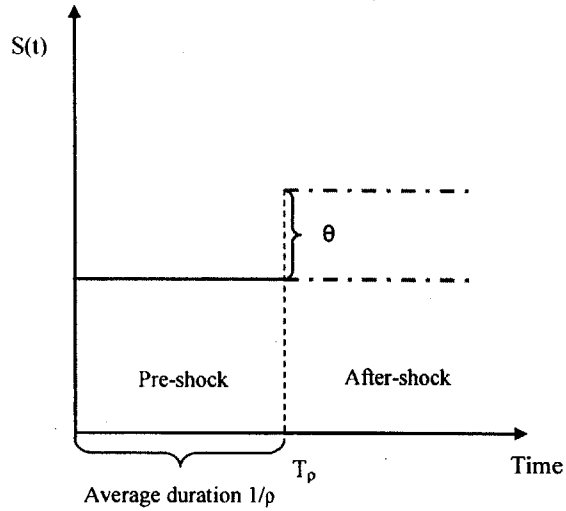
Figure 1-2: Asset supply might jump at random time T_ρ due to a negative shock.

Hence, while in the "long term" the price is expected to be $\frac{\delta}{r}$, in the "medium term" the demand curve is downward sloping as in (1.2). Campbell et al. (1993) find evidence consistent with this hypothesis by showing that returns accompanied by high volume tend to be reversed more strongly. Pastor and Stambaugh (2003) provide further evidence for this hypothesis by finding a role for a liquidity factor in an empirical asset-pricing model, based on the idea that price reversals are often provoked by liquidity shortages. Interestingly, Lou et al. (2011) shows that demand/supply shocks have temporary price effects even in the most liquid market of all, that for Treasuries. The mechanism involves the primary dealers, who are required to participate actively and to submit competitive bids in all auctions but whose risk-bearing capacity is limited, as captured in reduced form by (1.2).

Negative Shock. Since we are interested in speculators' response to negative shocks and in particular in how the strategic interactions among them might actually aggravate rather than mitigate these shocks, I assume that at time $t = 0$ the speculators become aware that a supply shock might hit the market some time in the future. I assume that at random time T_ρ, distributed according to a Poisson distribution with intensity $\rho > 0$, the uncertainty is resolved but with probability $1 - \varepsilon$ the shock does not occur. With complementary probability ε the market is hit by a shock of severity θ that increases supply and accordingly lowers the price. Hence, θ captures the *severity* of the shock, while $1/\rho$ is the *persistence* of uncertainty,

namely the average time before the uncertainty is cleared up, and ε can be interpreted as the *level* of uncertainty in the economy.[17] When ε is zero, as it is after T_ρ, speculators do not expect any future shock, but when ε becomes positive, as in the turmoil period $(0, T_\rho)$, investors are uncertain over the future price path, which affects their trading strategies dramatically.

As Figure 1-2 shows, once the first shock is realized at $t = 0$, speculators are uncertain about future market conditions: with probability $1 - \varepsilon$ the initial uncertainty shock has no consequences on the price, while with probability ε the asset price is depressed by the realization of the shock. I assume that the shock is commonly observed by all market participants, and when it hits the price moves instantaneously as dictated by (1.2).

1.2.1 Discussion of the Assumptions

The main assumptions of the model are worth some discussion.

First, let me highlight the interpretation of the uncertainty shock. In the asset pricing literature an increase in uncertainty is usually captured by time-varying second moments of the dividend or consumption growth processes (see for instance, Veronesi (1999), Bansal and Yaron (2004) and Bloom (2009)) or, recently, as uncertainty about the impact of government interventions (Pastor and Veronesi (2011b)).[18] In my model, by contrast, the fundamental value of the asset does not change, but due to jumps in supply the price may be severely affected even so. This way of modeling uncertainty is not intended to capture uncertainty about the fundamental value, but uncertainty about future market conditions, namely the price at which the asset can be traded. This makes it possible to show that speculators can destabilize financial markets by depressing the price below the level produced by the shock itself.

Intuitively, negative shocks in the form of an increase in supply could capture a situation in which other traders are forced to liquidate positions owing to margin calls or regulatory requirements. Coval and Stafford (2007) show empirically that funds suffering large investment

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[17] The assumption that the random time T_ρ is Poisson-distributed simplifies the analysis by guaranteeing that the speculators' problem is time-homogeneous.

[18] Bloom (2009) starts from the idea that uncertainty increases dramatically in the wake of major economic and political shocks like the Cuban missile crisis, President Kennedy's assassination, the OPEC oil-price shock, and the 9/11 terrorist attacks. The paper then structurally analyzes the shocks' effects in a firm-level model with a time-varying second moment. Also related to my model is the notion of an "anxious economy" introduced by Fostel et al. (2010). "Anxiety" is a state of the economy in which bad news increases the expected volatility of ultimate payoffs and prompts greater divergence among agents' opinion concerning these payoffs.

outflows create price pressure in the securities held in common by distressed funds because they tend to liquidate their positions.[19] Brunnermeier and Pedersen (2009) show that when higher margins and haircuts force de-leveraging and sales, this leads to further increases in margins, forcing still more selling.[20] Ellul et al. (2011), instead, investigates fire sales of downgraded corporate bonds in compliance with the regulations on insurance companies. Their collective need to divest downgraded issues may run afoul of a scarcity of counterparts, exacerbating the price fall.[21] I am interested in the *ex-ante* price effect due to the risk of a future shock, the time-pattern of the price recovery, and the speculators' equilibrium response.

Second, the model assigns a key role to long-term investors, who provide a downward-sloping demand to other market participants, even when the asset price is expected to decrease further. Interestingly, Vayanos and Woolley (2011) offer a model providing an explanation for this behavior. That is, rational investors buy assets whose expected returns have decreased because the assets that have fallen in price and are expected to continue underperforming in the short run are those held by investment funds expected to experience outflows. The anticipation of outflows makes these assets underpriced and guarantees investors an attractive return over a long horizon, which in my setting could motivate the long-term investors to provide downward-sloping demand to the speculators. The downward-sloping demand curve would also arise in a model in which some investor possesses private information about the asset's value (as in Kyle (1985) and Back and Baruch (2004)), or in limit order book markets (as in Biais and Weill (2009)).

Third, I have imposed two restrictions on the severity of the shock θ: that it is known at $t = 0$ and that it remains constant over time. The first restriction can be easily relaxed by assuming that the shock follows a compound Poisson process whose mean jump size is known to market participants. Relaxing the second restriction is the main object of Section 1.3.5. I will show that the model can accommodate situations in which the perceived severity of the shock varies over time.

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[19] In a similar vein, Khandani and Lo (2011) discuss how deteriorating credit portfolios and the need to reduce risk exposure compelled hedge funds to make large equity sales in the second week of August 2007, corresponding to a severe liquidity shock.

[20] Adrian and Shin (2010) find empirical support for this liquidity spiral in data on investment banks.

[21] Similarly, Greenwood (2005) investigates certain types of institutions, such as insurance companies or pension funds, that are required to sell bonds that lose their investment grade status, or stocks that are delisted or removed from a benchmark index.

1.3 Analysis

In this section I first characterize the speculators' decision problem. As a benchmark I investigate the single-speculator case: how a speculator would react to an increase in uncertainty if he were the only speculator in the market. Then, I consider how the equilibrium and the price path are affected by strategic interaction among speculators.

1.3.1 Formulation of the Speculator's Problem

In the case with a single speculator, he merely chooses his optimal trading strategy, buying (or holding) or selling (or not buying) the asset given its fundamental value $\frac{\delta}{r}$ and the expected shock that might lower the price at random time T_ρ.[22]

Let us first consider a speculator who has the opportunity to trade at time $t > T_\rho$: once all uncertainty is resolved. Let $V(a, t)$ denote the maximum expected discounted utility attainable by a speculator who is holding a portfolio $a \in [0, 1]$ at time t. The value function satisfies

$$V(a, t) = \mathbb{E}_t[\int_t^{T_\alpha} e^{-r(s-t)} \delta a\, ds + e^{-r(T_\alpha - t)} \{V(a(T_\alpha), T_\alpha) - p(T_\alpha)[a(T_\alpha) - a]\}], \qquad (1.3)$$

where T_α denotes the speculator's next trading opportunity. The expectation operator is taken with respect to the random variable T_α. The first term is the expected discounted utility flow enjoyed by the investor over the interval $[t, T_\alpha]$: the length of the interval $T_\alpha - t$ is an exponentially distributed random variable with mean $1/\alpha$. The second term is the expected discounted utility of the speculator from the time he next contacts a dealer, T_α, onward. At time T_α, the speculator readjusts his asset holdings from a to $a(T_\alpha)$. In this event he purchases $a(T_\alpha) - a$ in the market (or sells if this quantity is negative) at a price $p(T_\alpha)$. As in Lagos et al. (2011), the following lemma shows how to simplify the speculator's problem:

Lemma 1 (After-shock) *Suppose a speculator can trade at time $t \geq T_\rho$, then his optimal choice of asset holdings is $a(t) = 1$ if and only if*

$$u_a = \frac{\delta}{r + \alpha} > q(t), \qquad (1.4)$$

---

[22]Henceforth I refer simply to buying, implying that a speculator who already owns the asset will hold it, if it is optimal to buy; selling is considered optimal even when the non-owner speculator decides not to trade.

where

$$q(t) = \left[p(t) - \int_0^\infty \alpha e^{-(r+\alpha)s} p(t+s)\, ds \right].$$

Intuitively, u_a is the expected discounted value of holding the asset from time t until the next event, i.e. the next opportunity to trade which arrives at rate α; whereas $q(t)$ is the opportunity cost of holding the asset, i.e. the expected discounted forgone capital gain. By reducing the speculator's problem to a pointwise maximization, this characterization greatly simplifies the analysis. In other words, after the uncertainty in the market is resolved the speculator's decision is driven by a trade-off between the dividends from holding the asset and the potential capital gain from trading.

Now let me analyze the economy during the pre-shock period $[0, T_\rho)$. All the value functions and the prices in this interval before the realization of uncertainty, are denoted by the superscript "U" for the uncertainty phase. Following the same steps as in Lemma 1, it can be shown that an investor who accesses the market at time $t < T_\rho$ chooses his asset holdings $a^U \geq 0$ to maximize the following expression

$$\mathbb{E}\left[\int_t^{T_\alpha} e^{-r(s-t)} \delta a^U ds - \left(p(t) - e^{-r(T_\alpha - t)} p(T_\alpha) \right) a^U \right], \tag{1.5}$$

where the price at the next trading time T_α is

$$p(T_\alpha) = \mathbb{I}_{\{T_\alpha < T_\rho\}} p^U(T_\alpha) + \mathbb{I}_{\{T_\alpha > T_\rho\}} p^U(T_\alpha | T_\rho).$$

With some positive probability the speculator will come to the market before the resolution of the uncertainty $(T_\alpha < T_\rho)$, while with complementary probability he will be able to trade at the post-shock price $p^U(T_\alpha | T_\rho)$. There is only one difference between expression (1.5) and expression (1.4) for the case in which the speculator trades after the shock: namely, a speculator expects that the shock will have occurred by time T_α, when he is able to retrade the asset. The following lemma provides a simpler formulation of the speculator's problem.

Lemma 2 (Before-shock) *Suppose a speculator can trade at time $t < T_\rho$, then his optimal*

choice of asset holdings is $a^U(t) = 1$ if and only if

$$u_a^U = \frac{\delta}{r + \alpha + \rho} > q^U(t),\tag{1.6}$$

where

$$
\begin{aligned}
q^U(t) &= [p^U(t) - \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}(e^{-\rho(\tau_\alpha - t)}p^U(\tau_\alpha) \\
&\quad + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} p(\tau_\alpha | \tau_\rho)\, d\tau_\rho)d\tau_\alpha].
\end{aligned}
$$

Intuitively, the utility flow the speculator captures during the pre-shock interval $[0, T_\rho)$ is also discounted by the average duration of this interval (parameter ρ): the farther in the future the shock is expected (low ρ), the greater the incentive to hold the asset rather than selling in hopes of a capital gain, because the speculator will miss the dividends for a longer period. The price at which the speculator expects to trade takes into account the possibility that if he comes to the market at $T_\alpha < T_\rho$, the speculator has the opportunity to trade before the resolution of the uncertainty, while if he trades after the shock is realized, $T_\alpha > T_\rho$ then the speculator can condition his trading decision on the realization of the shock θ. The probability of being able to trade before or after the random time T_ρ will be influenced by the trading frictions captured by α and by the average length of the pre-shock period $1/\rho$, which explains why the trading frictions appear in the expression for $q^U(t)$. In fact, less trading frictions (higher α) allows the investor to trade right after the potential decline in price, which increases his capital gain. Hence he has a greater incentive to take advantage of the price swing.

I characterize the speculator's behavior in the following proposition:

Proposition 3 (Benchmark: single speculator) *It is strictly optimal for the speculator coming to the market at time $t \in [0, T_\rho)$ to sell or refrain from buying ($a^* = 0$) if and only if $\theta > \hat{\theta}$ and to buy otherwise ($a^* = 1$). As soon as the speculator can rebalance his portfolio at time $t \geq T_\rho$, it is optimal to buy the asset ($a^* = 1$) if the shock is realized.*

Proposition 3 characterizes the optimal trading strategy of a single speculator. He must decide whether to sell or hold the asset, and then decide when to buy it back. When there is a single speculator, however, the problem is simplified because the greatest capital gain is scored

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when the repurchase comes after the shock has hit. Buying back earlier would yield no capital gain, paying only the dividend. The only complication is that the speculator does not know when he will have a new trading opportunity, and there is uncertainty about the future price path: the shock might not occur at time T_ρ making it optimal to buy (or hold) the asset before T_ρ. In other words, when he has the opportunity to trade at time $t < T_\rho$, the speculator must decide whether to buy or sell, and forecast when he will have the opportunity to rebalance his portfolio. In particular, the speculator considers the possibility that he can buy back after the shock, but also the risk of loss if the shock does not occur at time T_ρ. The main implication of the benchmark is that with a single speculator only a high expected shock is likely to provoke preemptive selling. Specifically, Proposition 3 states that *only* when the shock is expected to be severe, i.e. greater than the threshold $\hat\theta$, will the speculator prefers to sell and repurchase when he gets the opportunity to trade after the shock, because the expected capital gain more than compensates for the forgone dividends.

Notice also that the threshold $\hat\theta$ is time-invariant; in particular it does not depend on the current price $p(t)$; whether he is in a bull or a bear market does not influence the speculator's trading strategy. We shall see that this is not so when strategic interaction among speculators is allowed for. The next corollary shows the comparative statics with respect to the main parameters of the model:

Corollary 4 (Comparative statics) *The speculator's net benefit from selling the asset decreases with the persistence of uncertainty $1/\rho$ and increases with the level of uncertainty ε, with market depth λ, and if the dividend δ is sufficiently small it increases with α.*

The parameters ε influences the expected magnitude of the shock and λ its effect on the price. Hence, it is not surprising that higher values of these parameters are associated with a greater likelihood of selling before time T_ρ. Higher ρ means a shorter average duration of the pre-shock period, which increases the speculator's incentive to profit from the price swing because the expected time during he forgoes dividends is shorter. A similar intuition explains why an increase in the arrival rate of trading opportunity α heightens the speculator's incentive to sell after the initial shock at $t = 0$. In the next section, I show that trading friction has a non-monotonic effect when a number of speculators interact.

1.3.2 The Amplification Mechanism

This section analyzes the main mechanism posited in the paper: namely, that the impact of uncertainty may be amplified by the endogenous volatility generated by speculators' trading in the same direction.

As in the previous section, an equilibrium is characterized in two steps: solving first for the equilibrium after uncertainty is resolved for every possible T_ρ and then for the equilibrium during the pre-shock period, i.e. prior to T_ρ. One simplification of the single-speculator case is that the price path can be computed easily and does not depend on other speculators' dynamic trading strategies. But when interaction among speculators is allowed for, this simplification no longer applies. In other words, asset price volatility is *endogenous*, because it depends as before on the potential shocks to the asset supply, but now, additionally, on speculators' trading strategies. Selling in response to an increase in uncertainty puts pressure on the price and determines the extent of the price swing. Hence, not only are expectations about potential shocks important in predicting the response of speculators to greater uncertainty, so are their beliefs about how the other speculators will respond.

In spite of this difficulty, we can derive clear predictions on equilibrium trading strategies and on price path. I start by defining the equilibrium:

Definition 5 *An equilibrium is a time-path $\left(\left\{a^U\left(t\right)\right\}, \left\{a\left(t\right)\right\}, \left\{p\left(t\right)\right\}\right)$ that satisfies (1.4), (1.6) and market clearing (1.2) given initial conditions $p\left(0\right)$ and $x\left(0\right)$. A "leaning-against-the-wind" equilibrium is one in which the price path is increasing over both intervals $[0, T_\rho)$, and $(T_\rho, \infty]$. A "cashing-in-on-the-crash" equilibrium is one whose price path is decreasing over the interval $[0, T_\rho)$ and increasing over $(T_\rho, \infty]$.*

The previous definition identifies two possible types of equilibrium. In the "*leaning-against-the-wind*" equilibrium, speculators expect others to buy the asset over the interval $[0, T_\rho)$, which drives the price upward and makes it profitable to buy. A "cashing-in-on-the-crash" equilibrium emerges whenever the price swings make it optimal to take a capital gain by selling over $[0, T_\rho)$ and buying back at $T_\alpha > T_\rho$. For concreteness, I assume that if they are indifferent between buying and not trading, the speculators do not trade. I show that, depending on the parameters, either type of equilibrium can emerge when speculators interact and then derive a

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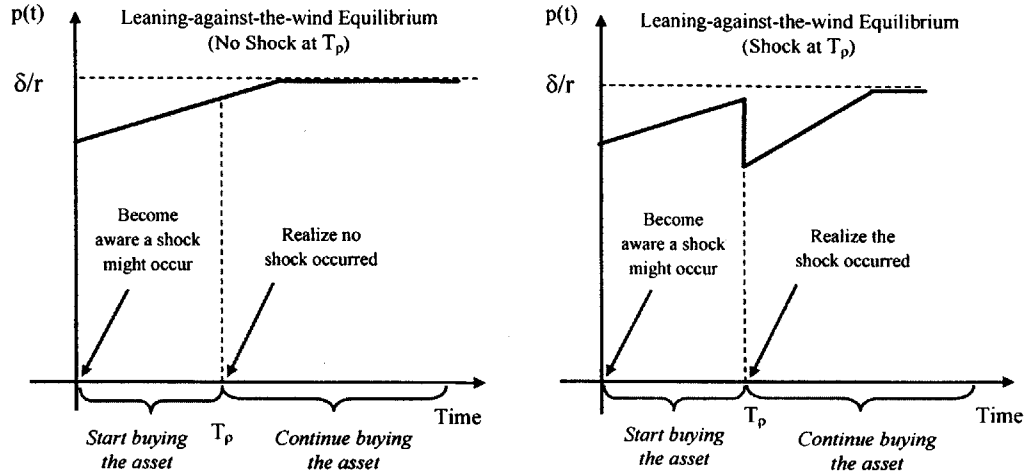
Figure 1-3: The price path in a "*leaning-against-the-wind*" equilibrium where the shock does not occur (left panel) and where it does (right panel) at random time T_ρ.

unique equilibrium in Section 13 by positing that the speculators' perceptions of the severity of the crisis θ fluctuate over time. As we can see in Proposition 8, when the price goes too low to make it profitable to sell and repurchase, they stop trading and the market freezes.

When the speculator interacts with other speculators, the price is endogenously determined by the others' trading strategies, I first compute the price path under the two equilibria. The fraction $x(t)$ of speculators that are long on the asset evolves according to

$$
\dot{x}(t) = \begin{cases} -\alpha x(t) & \text{if investors sell} \\ \alpha(1-x(t)) & \text{if investors buy} \end{cases},
$$

that is, the price rises if speculators start buying and falls over time at rate α if they start selling in response to the uncertainty shock. The next lemma shows the price path in the two equilibria.

Lemma 6 (Price dynamics) *If $p(t) < F$, in the "leaning-against-the-wind" equilibrium the price rises over time at rate α. In the "cashing-in-on-the-crash" equilibrium, it falls at rate α over the interval $[0, T_\rho)$ and rises at the same rate for $t > T_\rho$. In both equilibria, the price may jump at time T_ρ in the event of a shock.*

Lemma 6 shows that in the first type of equilibrium the price rises over both intervals $[0, T_\rho)$

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and (T_ρ, ∞); speculators react to the uncertainty shock at $t = 0$ by purchasing the asset, driving the price up. In the "cashing-in-on-the-crash" equilibrium, by contrast, the price declines at a rate α over the interval $[0, T_\rho)$, because speculators sell off their holdings when they get the opportunity to trade, building up selling pressure. The lemma also shows that trading friction affects the speculators' objective in two ways. It has a direct effect, insofar as α determines the arrival of trading opportunities. And it affects the speed of the price movements, which in turn influence the gains accruing to the speculators.

This sets the stage for the first principal result, characterizing the conditions under which speculators trade in the same direction of the shocks and so amplify their effects.

Proposition 7 (Strategic Interactions) *Consider a speculator who can trade at time $t < T_\rho$:*

(i) There exist two severity thresholds $\bar{\theta}(p(t))$ and $\underline{\theta}(p(t))$ such that it is strictly optimal for him to sell when $\theta > \bar{\theta}(p(t))$ and to buy when $\theta < \underline{\theta}(p(t))$, if he expects other speculators trading after time t to buy and sell, respectively.

(ii) The thresholds are decreasing in the price $p(t)$ and $\underline{\theta}(p(t)) < \bar{\theta}(p(t))$.

Proposition 7 parameterizes the model according to the severity of the shock θ and identifies two dominance regions: one for which it is always optimal to buy $(\theta < \underline{\theta}(p(t)))$ and the other in which it is optimal to sell $(\theta > \bar{\theta}(p(t)))$, regardless of what other speculators may do in the future. In the intermediate region, namely for $\theta \in [\underline{\theta}(p(t)), \bar{\theta}(p(t))]$, the speculator's response to the increase in uncertainty depends crucially on his expectation of what other speculators will do when they get the opportunity to trade. Intuitively, this proposition highlights the importance of the strategic interactions among speculators. Their strategies depend critically on what other speculators plan to do in the future. When the price is expected to come down in anticipation of the shock, speculators amplify the shock by provoking a fire sale. In short, negative shocks that are only expected for the future could cause a financial run today.

In a *leaning-against-the-wind* equilibrium, speculators start providing liquidity to the market by purchasing the asset, which gradually increases the price, although it may plunge at T_ρ if a shock is realized, as is shown in Figure 1-3. In expectation of a rising price, speculators stabilize the market with purchases as long as the price is below the fundamental value of the asset

p(t) ▲   Cashing-in-on-the-crash Equilibrium
(No Shock at T_ρ)

δ/r

p^* Realize no
shock occurred

T_ρ Time

Start selling   *Market*   *Start buying*
the asset   *Freezes*   *the asset*

p(t) ▲   Cashing-in-on-the-crash Equilibrium
(Shock at T_ρ)

δ/r

p^* Realize the
shock occurred

T_ρ Time

Start selling   *Market*   *Start buying*
the asset   *Freezes*   *the asset*
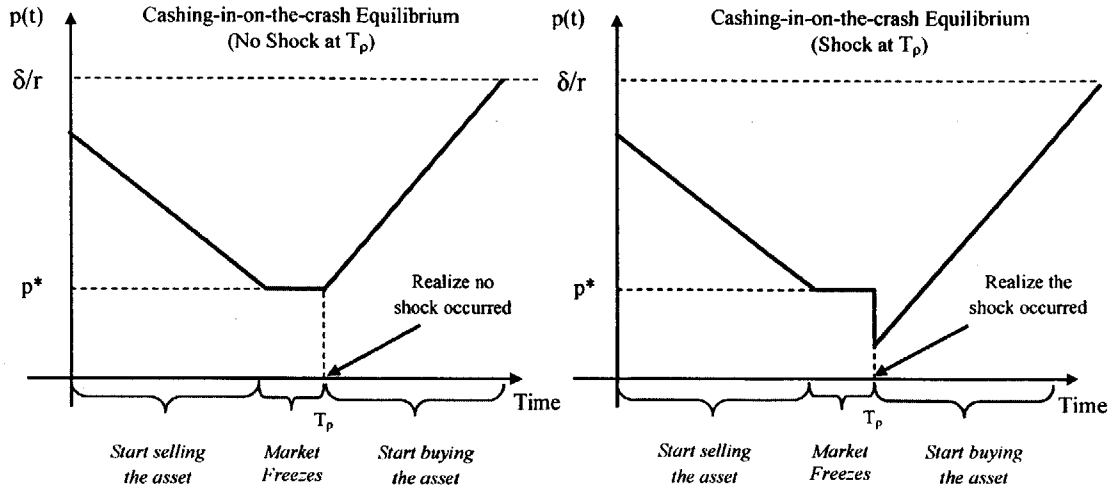
Figure 1-4: The price path when a "*cash-in-on-the-crash*" equilibrium emerges and the shock does not occur at random time T_ρ (left panel) and when it does occur (right panel). The flat line in the right panel captures the market freeze when the price reaches the value of p^*.

$(p(t) < \frac{\delta}{r})$, correcting the temporary mispricing. In the *cashing-in-on-the-crash* equilibrium, the price begins to fall as soon as uncertainty about the future price path emerges. The strategic interactions among speculators also clarify that an identical expected future shock may have very different present implications depending on the speculators' response.

The proposition also brings out another property of the equilibrium. The thresholds that define the intervals in which one equilibrium or both emerge are decreasing in the price. This means that markets where the asset is relatively over-valued are more vulnerable to uncertainty shocks.

The next proposition explicitly characterizes the *cashing-in-on-the-crash* equilibrium by identifying three phases: *crash, market freeze,* and *recovery*.

Proposition 8 (Equilibrium) *Suppose $x(0)$ is sufficiently high and consider a speculator who can trade at time t :*

(Crash) If $t < T_\rho$ and the speculator expects others to sell the asset in the future, he sells his holdings immediately, provided that $p > p^*$;

(Market Freeze) There exists a unique cut-off for the price p^* such that if it reaches this level trading comes to a complete halt, i.e. $\dot{x}(t) = 0$ and $\dot{p}(t) = 0$.

(Recovery) If $t \geq T_\rho$, then it is optimal to buy the asset $(a^* = 1)$ provided that $p(t) < F$.

Proposition 8 is represented in Figure 1-4. The first part of the proposition describes the crash phase, showing that when speculators have the chance to trade prior to the resolution of uncertainty, they will liquidate their positions if they expect a decreasing price path in the future and if the price is still sufficiently high. The second result of Proposition 8 shows there exists a price p^* at which the market freezes. Intuitively, this is the price that makes speculators indifferent between selling and holding. Interestingly, in my model the market can freeze even in the absence of asymmetric information. In other words, an uncertainty shock may not only amplify of negative shocks and destabilize financial markets, but also dry up liquidity completely. As the right panel in Figure 1-4 illustrates, this is more likely when uncertainty is persistent. Finally, the last part of the proposition shows that once the shock has occurred, it becomes optimal for speculators to purchase the asset as long as its price is below the fundamental value. Equivalently, one could interpret this result as capturing liquidity hoarding by the speculators in order to strategically time the bottom of the market after the shock.[23]

The prediction of the proposition is in line with the evidence of Ellul et al. (2012) that during episodes of market turmoil institutional investors with short trading horizons (proxied by portfolio turnover) sell their holdings more aggressively than those with longer horizons. This puts price pressure on the stocks held chiefly by short-horizon investors, which therefore undergo sharper price drops and subsequent upturns than stocks held mostly by long-horizon investors. Overall, the evidence indicates that investors with short horizons amplify the effects of negative market-wide shocks by demanding liquidity at times when other potential buyers' capital is scarce. This is the empirical counterpart to the "cashing-in-on-the-crash" equilibrium identified by the previous Proposition.

Second, the interaction between speculators and long-term investors generates momentum and reversal in a cashing-in equilibrium. In fact, the price decreases steadily until the shock hits, at which point it jumps down and then reverts toward the fundamental value.

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[23] This insight is related to Diamond and Rajan (2011) which show that when some banks may be forced to sell assets in the future this can reduce the current price of illiquid assets sufficiently that these banks have no interest in selling them. Moreover, to profit from the future fire sale potential buyers might strategically hoard liquidity. Their mechanism relies on the assumption that these potential buyers have finite borrowing capacity (as in Shleifer and Vishny (1997)). In my model, instead, the strategic interaction among speculators drives the dynamics of the asset price.

At this point, it is interesting to investigate how the price path changes with trading friction. The following proposition highlights the relationship between α and price dynamics:

Proposition 9 (Trading Frictions and Price Fluctuations) *In a cashing-in-on-the-crash equilibrium less trading friction, i.e. higher α, leads to a greater decline in the asset price for $t < T_\rho$ and a faster recovery towards the fundamental value for $t \geq T_\rho$.*

The previous proposition follows from Lemma 6 and Proposition 8. It implies that we should expect a sharper decline in asset prices when speculators have access to faster trading technology. This is because a larger fraction of speculators will have the chance to sell in hopes of timing the bottom of the market. This result suggests that high-frequency traders can have a very considerable impact on price stability, which may prompt sporadic market crashes like the one that occurred in May 2010. However, in a low-friction market the price recovers faster after the shock at T_ρ. In other words, less trading friction may imply deeper but less persistent price declines in periods of high-uncertainty.

The role of the three main assumptions of the model bears emphasis here. First, in absence of the uncertainty shock, i.e. for $\varepsilon = 0$, the speculators would behave exactly like long-term investors, purchasing the asset as long as the price is below its fundamental value. Second, the downward-sloping demand curve is needed in order to make the price sensitive to the speculators' trading strategies; without it, the price would not change in response to the supply shock. And lastly, the presence of trading friction allows for a slowly changing price, which results in momentum and reversal.

1.3.3 The Role of Liquidity, Trading Frictions and Uncertainty

The foregoing investigated two possible equilibria. The present section considers which market and security characteristics make one or the other more likely emerge. To obtain the predictions, I inquire into the effect of trading frictions and uncertainty on the speculators' incentives, ultimately reaching the following result:

Proposition 10 (Comparative Statics) *The amplification of a negative shock is more likely to occur in illiquid markets (high λ). Moreover, there exists an $\underline{\alpha}$ such that the speculators'*
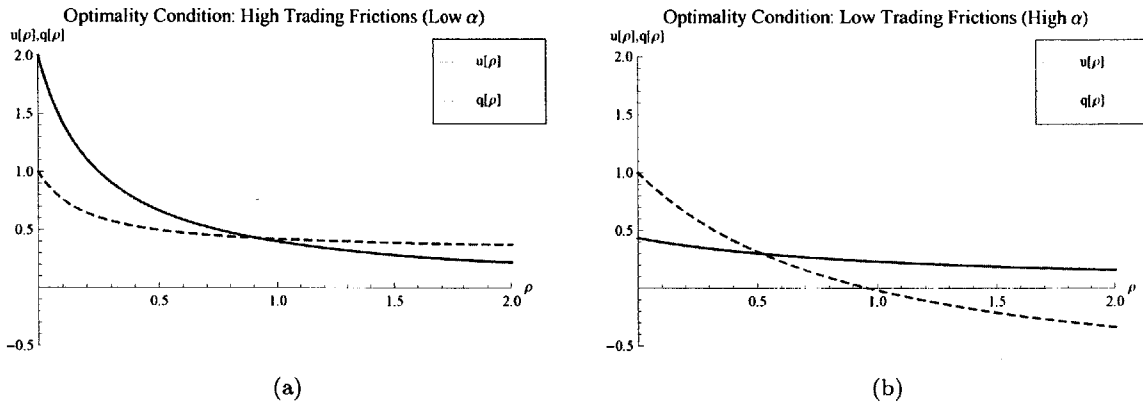
Figure 1-5: The effect on speculators' incentives of the persistence of uncertainty ρ for low and high value of the trading frictions α.

incentive to sell at $t < T_\rho$ increases with ρ if $\alpha < \underline{\alpha}$; while there exists a $\bar{\rho}$ such that the effect of trading frictions α is not monotone for $\rho > \bar{\rho}$.

The effects of market depth λ follows from the fact that in less liquid markets the effect of the shock and of the price pressure exerted by other speculators is expected to be greater. This increases the expected capital gains to speculators from strategically selling their holdings at $t < T_\rho$. The intuition for the other results in the previous proposition can be better understood by analyzing Figures 1-5 and 1-6. Figure 1-5 depicts the two curves, $u_a\,(a)$ and $q\,(t)$, that determine the investors' optimality condition found in Lemma 2 and shows an interesting interaction between trading frictions as captured by parameter α and the arrival rate of the shock ρ. Even if an increase in ρ decreases both $u_a\,(a)$ and $q\,(t)$, it is not clear at what point it will become optimal to sell rather than buy, as this depends on the interaction between trading frictions α and the arrival rate of the shock ρ. When trading frictions is very great (low α) as pictured in Panel (a) the price is expected to decline very slowly, which means that the expected return to "cashing in on the crash" is low. This is why it is optimal to sell at $t < T_\rho$ only if ρ is high enough, that is, to the right of the intersection between the two curves. On the other hand, when investors can access the market almost continuously – the scenario in Panel (b) – then the incentive to sell is greater when ρ is low so that the capital gain $q\,(t)$ is greater than the value $u_a\,(q)$ obtained by holding the asset.

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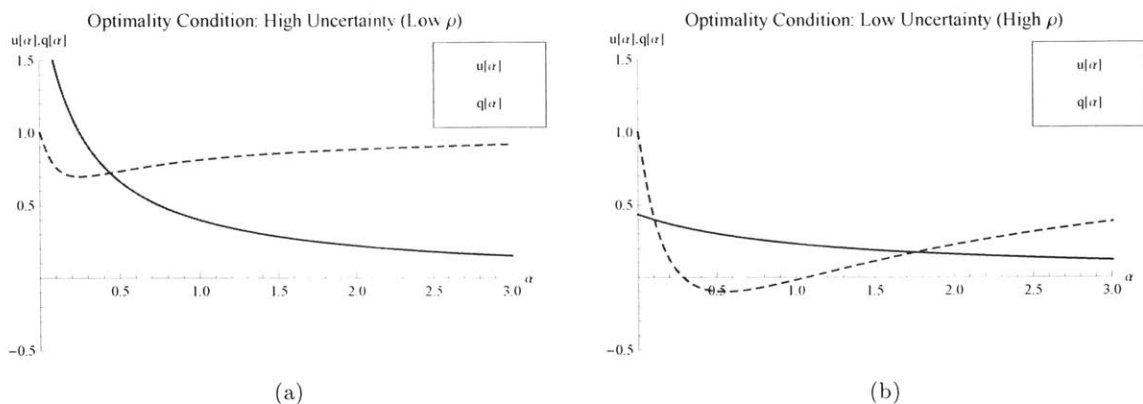
Figure 1-6: The effect of trading frictions α on speculators' incentives for low and high values of the persistence of uncertainty ρ.

To illustrate the second part of proposition 10, Figure 1-6 shows the two curves $u_a (a)$ and $q(t)$ as a function of the trading frictions α in two different scenarios: low uncertainty and high uncertainty (measured by the average time ρ before uncertainty is resolved). Panel (a) shows that if the shock is expected to come very far in the future (low ρ), then only traders with continuous access to the market have an incentive to profit from the price swings, because the speculators will have the opportunity to sell just before the shock and repurchase immediately afterward, forgoing the cash flows for a shorter period of time. Panel (b), instead, shows that speculators' incentives to profit from the crash vary in a non-monotonic fashion with the magnitude of trading frictions: only when α is very high or very low will speculators sell their holdings, amplifying the effect of the initial shock. Alternatively, when α is intermediate, speculators who have the opportunity to readjust their holdings anticipate that they will retain the assets for a longer time (since the average holding period of the asset is $1/\alpha$), which is not fully compensated by the capital gains in a scenario in which ρ is high (because the shock will hit before any significant movement in price). As a consequence, speculators choose to hold rather than sell.

Intuitively, the trading frictions play two opposing roles. First, they determine how fast the speculator can trade and exploit the price swing. Second, they determine how much the price will change before the shock is realized. Low trading friction always heightens the incentive to profit from the capital gain, because the trader can profit the most from the price swing thanks

to the opportunity to sell when the price is high and buy back immediately following the shock when the price is at its minimum. This is the case, for instance, of traders who have practically continuous access to the market. At the same time Panel (b) shows that "cashing in on the crash" can also occur when traders operate in markets in which it is difficult or costly to submit orders and have a greater incentive to take advantage of the price swing, because even if he may not get the chance to trade right after the shock, in a high-friction market (such as OTC markets) this is less of a concern because the price will recover very slowly, which means that the capital gains opportunity persists for a longer time. This case becomes more important when the uncertainty window is shorter, because the dividends forgone will be less. This no longer holds for intermediate values of α, and speculators will prefer to buy the asset and enjoy its dividend flows rather than selling it.

These findings square with the evidence on the actual behavior of high-frequency traders in financial markets. For instance, Zhang (2010) shows that high-frequency trading is positively correlated with stock price volatility after controlling for firm-fundamental volatility and other exogenous determinants of volatility. Interestingly – as my model predicts – the result is even stronger during periods of high market uncertainty (when the VIX index is above its historic median). Consistent with concerns about high-frequency traders imposing adverse selection on other investors, Hendershott and Riordan (2011) find that HFT liquidity-supplying orders are adversely selected in terms of the permanent and transitory components as these trades run against permanent price changes and with transitory pricing errors.

One vivid example of disappearing liquidity is the flash crash of May 6, 2010, when the Dow lost nearly 1,000 points (about 9.2%) in a matter of minutes. After five months of investigations, the SEC and the Commodity Futures Trading Commission issued a joint report on the causes.[24] The main cause identified was a single sale of $4.1 billion in futures contracts by a mutual fund, Waddell & Reed Financial, in an aggressive attempt to hedge its investment position. This event can be captured by my initial shock at $t = 0$ and the resulting increase in uncertainty about the asset price. The report also found that "high-frequency traders quickly magnified the impact of the mutual fund's selling." How? The report noted that "HFTs began to quickly buy and then resell contracts to each other — generating a 'hot-potato' volume effect as the

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[24] "Findings Regarding the Market Events of May 6, 2010". 2010-09-30.

same positions were passed rapidly back and forth." This resembles the mechanism proposed in my model. While some firms exited the market, high-frequency firms that remained in the market exacerbated price declines because they "escalated their aggressive selling during the downdraft."[25]

1.3.4 Sand in the Wheels: the Tobin tax

The recent economic crisis has rekindled interest in James Tobin's proposal to "throw some sand in the wheels" of speculators. Specifically, on December 3, 2009, the "Let Wall Street Pay for the Restoration of Main Street Bill" to impose a tax on US financial market securities transactions was presented in the House of Representatives. Similarly, in September 2011 the European Commission proposed instituting a financial transaction tax within the 27 EU member states by 2014. Such taxes would be akin to Pigovian taxes, obliging speculators to internalize the costs of the systemic risk they generate. The advocates of the transaction tax believe that it would calm the self-fulfilling financial turmoil we have experienced in recent years; however, many market practitioners have opposed it, maintaining that it would affect market liquidity adversely or cause financial transactions to shift into other jurisdictions.

To study how a transaction cost would affect speculators' trading strategies and the asset price, I introduce a transaction cost $c > 0$ paid by speculators whenever they modify their portfolio holdings. That is, a speculator who buys the asset pays $p(t) + c$, one who sells receives only $p(t) - c$.

I can extend the analysis proposed in the previous section to analyze the conditions under which speculators decide to liquidate their positions when they are subject to a transaction tax. In the next proposition, I show that the introduction of a tax on financial transactions might reduce the fragility of the market: speculators need to expect a more severe negative shock (higher θ) to induce a cashing-in equilibrium. However, according to Proposition 11 speculators might be induced to refrain from buying if the tax is sufficiently high.

Proposition 11 (Tobin tax) *Suppose a speculator who has the opportunity to trade at time t expects other speculators to sell the asset in the future. A more severe shock θ is needed to*

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[25] See "How a Trading Algorithm Went Awry" published by the *Wall Street Journal* on October 2, 2010.

induce him to sell as well when $c > 0$. Moreover, there exists a threshold c^* such that if $c > c^*$ the speculators refrain from trading at all.

Proposition 11 shows that the effect of the tax on financial transactions on speculators' trading strategies is twofold. On the one hand, it can reduce the gain from selling in response to an increase in uncertainty. In fact, by reducing the capital gains speculators expect to realize from selling and then buying back after the shock, it reduces price volatility. On the other hand, a transaction cost above the threshold c^* induces speculators to refrain from trading until uncertainty is realized, hoping to buy the asset at a lower price in the event of a shock.

A different argument, based on the trade-off between congestion and liquidity, which sets out the rationale for policies to avoid extreme price movements, has been proposed by Afonso (2011). Specifically, she argues in favor of trading halts and circuit breakers that interrupt trading when there is a significant imbalance between buy and sell orders or when asset prices decline beyond trigger levels.[26] These instruments, by increasing search frictions during downswings, reduce the effect of congestion, resulting in a lower price discount and in a more liquid market. My result does not depend on negative externalities between speculators – the congestion effect –but follows from the impact of the transaction cost on capital gains: it is more costly for the speculators to exploit temporary price fluctuations. Moreover, Proposition 11 shows that the reduction in fragility might be achieved at the cost of diminishing participation of speculators. This means that even if in equilibrium speculators would have purchased the asset from $t = 0$ onwards, if the tax is excessive they might not.

Up to now I have assumed that only the speculators are affected by the introduction of the Tobin tax. Actually, though, it would affect all market participants and might discourage potential liquidity providers. The model can be extended to accommodate this possibility by assuming that long-term investors' demand function becomes steeper as the transaction cost increases, that is, $\lambda'(c) > 0$. In other words, the transaction cost leads some fraction of long-term investors to leave the market. The next proposition shows that, in this case, the Tobin tax might have a destabilizing effect on financial markets.

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[26]For instance, circuit breakers were adopted by the New York Stock Exchange following the 1987 stock market crash to reduce volatility and promote investor confidence.

Proposition 12 (Tobin tax and liquidity) *There exists a $\bar{\lambda}$ such that if the introduction of a transaction cost c increases λ above $\bar{\lambda}$, then a Tobin tax increases the speculators' incentive to sell at $t < T_\rho$.*

Proposition 12 follows from the comparative statics results in Proposition 10: since speculators have a greater incentive to amplify market shocks in less liquid markets, if the tax on financial transactions reduces participation by long-term investors, speculators expect to make more capital gains by selling in response to the uncertainty shock. Hence, the previous proposition highlights an important factor to weigh in seeking to understand the effectiveness of a Tobin tax: how to target such a measure to speculators and not to potential liquidity providers.

1.3.5 Equilibrium Uniqueness

Overview. The baseline version of the model, which assumes that all speculators have the same information about the severity of the shock θ when they have the opportunity to trade, shows that two types of equilibrium are possible. It also serves to analyze the market characteristics that influence speculators' strategies. Now, instead, we examine how the results are affected when the severity of the shock changes over time. This section shows that a time-varying shock θ, by introducing some heterogeneity in the speculators' perception of severity, leads to a unique equilibrium that has several intuitive properties.

Formally, I assume that the perceived severity of the shock θ starts at a value $\theta_0 > 0$ time $t = 0$ and then evolves according to the commonly observed geometric Brownian motion[27]

$$\frac{d\theta_t}{\theta_t} = \mu dt + \sigma dW, \tag{1.7}$$

where μ and σ are constants.[28] The trend μ captures how the mean changes over time; the variance σ measures the size of the random component, specifically, how quickly θ spreads out. This captures the idea that investors expect a shock, but that the situation may either improve

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[27] Frankel and Burdzy (2005) show that a similar argument can be used when θ_t follows an arbitrary mean-reverting process with time-varying drift μ and volatility σ.

[28] A similar approach has been proposed by Frankel and Pauzner (2000) to derive uniqueness in a model of sectorial choice with external increasing returns. In our setting, the speculator's payoff depends on the other speculators' behavior through the market-clearing price. The endogeneity of the price provides novel insights absent in Frankel and Pauzner (2000).

$(\mu < 0)$ or deteriorate $(\mu > 0)$ over time; and market conditions may evolve slowly (low σ) or quickly (high σ). Introducing this dynamic aspect of severity creates heterogeneity in the conditions under which speculators trade. Those trading at time t might observe a different θ than those trading at $t + dt$. In other words, they cannot be sure that others will hold the asset until the next trading opportunity because the expected shock can become more severe in the future, i.e. θ might increase.

Intuitively, such a set-up captures situations in which there is uncertainty about how severe the shock will be; for instance, it could depend on policy measures to counter the repercussions of the shock; or the uncertainty could simply reflect the fact that speculators do not know the full extent of the crisis at $t = 0$ but gradually discover it. For example, in the European debt crisis speculators expected the Greek economy to suffer large losses, but their extent depended crucially on several factors whose impact was unknown in early 2010, e.g. the ECB interventions and the Greek elections. In other words, a speculator trading in April 2010 (when Papandreou called for a rescue package) had a different information set from one trading in July (when the Greek Parliament passed the pension reform required by the European Union and the IMF) or in June 2011 (when the Greek debt was downgraded by Standard and Poor's from B to CCC). I exploit this heterogeneity to derive a unique equilibrium. In fact, it triggers a contagion argument that leads to equilibrium uniqueness as shown by the next proposition.

Proposition 13 (Unique Equilibrium) *When the severity of the shock θ follows (1.7) then there exists a unique threshold $\theta^* (p(t))$, such that cashing in on the crash is optimal if and only if $\theta > \theta^* (p(t))$; while leaning-against-the-wind emerges as an equilibrium for $\theta < \theta^* (p(t))$.*

Figure 1-7 describes the main intuition behind the proposition. At the right of the threshold θ^* speculators start liquidating their position; while when they expect the severity of the shock to be smaller than θ^*, they find it optimal to buy or hold the asset. Intuitively, if the shock is expected to be sufficiently severe, namely $\theta > \theta^*$, capital gains will be greater and it will be optimal for the speculators to liquidate their positions. But when the shock is expected to be mild, namely $\theta < \theta^*$, they prefer to hold the asset or buy it below the fundamental price in order to capture the dividend flow.

The equilibrium depicted in Figure 1-7 has three main properties.
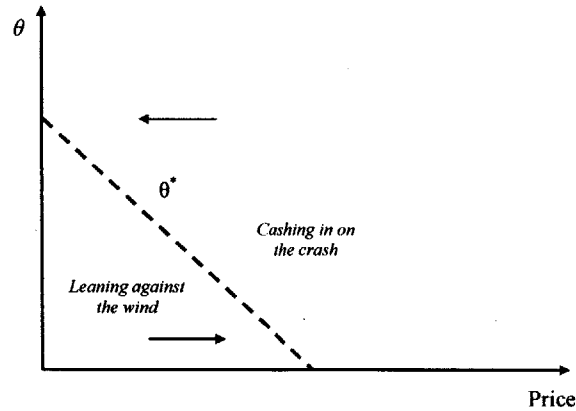
Figure 1-7: The unique equilibrium

Property 1: *Fragility*. Marginal perturbations to speculators' perceptions about the shock's severity may have discontinuous effects.

Property 1 is the main implication of this equilibrium: when traders are uncertain about the future price path, financial markets become more fragile. The model captures fragility in two ways. First, the baseline model exhibits multiple equilibria so that fluctuations in market participants' sentiment can induce drastic changes in the provision of liquidity and in the resulting response to shocks during periods of high-uncertainty. Second, the model outlined in this section shows how small changes to the speculators' perception of the severity of future shocks induce large changes in aggregate outcomes. In fact, whereas to the left of the threshold θ^* speculators respond to a decline in price by absorbing the excess supply, small changes to their perceptions of how severe the shock may be are sufficient to shift the parameter θ above the threshold, at which point they start liquidating their long positions and depress the price further by amplifying the initial shock. This also explains why traders may react differently under similar market conditions and why crashes may occur. For instance, for several European countries that were close to default in 2011 and 2012 due to soaring government financing costs, rapidly widening spreads were not justified by changes in fundamentals but were a signal of changed market assessments of their creditworthiness.

Property 2: *Dynamics*. The price declines to the right of the threshold θ^* and increases to the left.

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Property 2 shows that the equilibrium also has implications for the price path. The arrows in Figure 1-7 show that to the right of the threshold θ^* the price will decrease over time, because that is the region in which speculators are selling off their holdings, putting pressure on the price. To the left of θ^*, instead, speculators' demand for the asset will push the price up over time. In contrast to the previous subsection, we can now obtain more precise predictions about the price path.

However, the threshold θ^* depends on the equilibrium price and this is highlighted by the next property.

Property 3: *Trend.* Bull markets are more likely than bear markets to undergo waves of selling pressure due to expectations of the same shock in the future.

A further implication of this analysis is that one should expect speculators to react differently depending on market conditions: in a bull market, when the price is high, it is more likely that a small amount of uncertainty will prompt speculators to sell. Since the price is already high, even a small dose of uncertainty heightens the incentive to sell and realize a capital gain, which also means that a smaller shock will be sufficient to induce speculators to amplify the initial shock. In a bear market, by contrast, the cash flow from holding the asset is more attractive because the price is too low to generate any significant capital gain. This finding is interesting because it implies that the prices of assets with correlated.fundamentals could evolve very differently depending on how high each asset price is to begin with.

1.4 Empirical Analysis

1.4.1 Overview

To assess the impact of uncertainty on investors' behavior empirically and in particular to test whether investors can amplify market shocks, one must identify an exogenous shock to the level ε of uncertainty in the economy. To this end I take the sudden turbulence in the euro area as a proxy for an increase in uncertainty and I exploit cross-sectional variation among issuers and funds. This section provides empirical evidence on the main predictions of the model by analyzing the behavior of Money Market Funds (MMFs) during the sovereign debt crisis.

In recent years money market funds have played a critical role in aggravating global financial problems. They have been blamed for exacerbating first the financial crisis in 2007-2009 and then the European debt crisis, owing to their fundamental role in the short-term financing market. For this reason, it is particularly important to analyze their behavior as a possible source of heightened systemic risk. In the words of the Financial Stability Oversight Council report of 2011:

> "Structural vulnerabilities in money market funds and tri-party repo amplified a number of shocks in the financial crisis. Reforms undertaken since the crisis have improved resilience, and money market funds report *de minimis* exposure to Greece, Ireland, and Portugal; however, amplification of a shock through these channels is still possible."[29]

The European debt crisis provides an ideal setting to investigate the reaction of investors to an abrupt increase in uncertainty; the period in which the crisis occurred and the type of institutions and securities most strongly affected are clearly identifiable.

My empirical analysis consists of two parts. First, I exploit the high level of granularity of my data to provide evidence at issuer level about what drives the funds' trading strategies. Funds are more likely to sell assets issued by institutions for which the behavior of other funds is more relevant. In other words, one of the main drivers of funds' decision to sell some assets rather than others is complementarity among funds. This result confirms the model's main predictions. Further, the analysis clearly shows how the funds' behavior has aggravated the situation facing European institutions: shortening the maturity of their assets and increasing the yields on their short-term borrowing requirement. These consequences cannot be explained by an increase in risk, funds' capital constraints or heterogeneous incentives to diversify their portfolios.

Second, I provide fund-level evidence to support the time-series pattern predicted by the model. In response to a spike in uncertainty, MMFs liquidated substantial positions in the euro area, only to reenter months later at more profitable terms. I can determine which types

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[29]Financial Stability Oversight Council 2011 Annual Report (available at http://www.treasury.gov/press-center/news/Pages/FSOC-Annual-Report-2011.aspx)

of funds are likely to behave like the speculators of my model. Taking portfolio liquidity as a proxy for sophistication, I show that the *less* liquid funds are significantly more likely to first reduce and then significantly increase their exposure than funds that can readily liquidate their positions.

1.4.2 Bringing the Model to the Data

My quasi-experiment is the spike in uncertainty about the future of the euro area, which represents the ε shock in the model. The VIX index and the European political uncertainty index proposed by Baker et al. (2011) (Figure 1-8) are used to identify October 2011 as the month when the situation in Europe deteriorated sharply, becoming a source of significantly greater concern for market participants. The pinpointing of October 2011 is confirmed by the VIX index, which traded as high as 46, well above its long-run average of 20. This was due to: (1) the announcement that Greece could not meet the 2011 and 2012 deficit targets as agreed with the Troika; (2) Papandreou's call for a referendum on the rescue plan agreed upon just days earlier.

I can also identify, in my sample, the time when the uncertainty was resolved. In February 2012 the European Central Bank introduced its second long-term refinancing operation (LTRO) to pump liquidity into the banking system. The first LTRO 3-year tender in December 2011 had an uptake of €489 billion, of which about €300 billion was used to retire loans taken out via shorter-term ECB lending facilities and only about €190 billion created fresh liquidity. In February 2012, the ECB held a second auction providing euro-area banks with another €529.5 billion for a period of three years at a rate of just 1 percent. This second LTRO auction saw 800 banks take part, compared with 523 in the December auction. Since these operations by the ECB were recognized as crucial to improving the stability of European financial institutions, I posit that uncertainty fades February 2012, which matches the time T_ρ in the model.

To distinguish between the effect of increased risk and the strategic motive behind funds' trading strategies, I focus on the period during which money market funds are already not exposed to the riskier European countries: Portugal, Italy, Ireland, Greece and Spain. Figure 1-9 tracks the fraction of assets under management invested in these countries by the U.S. money market funds. It clearly shows that in July 2011 the funds' direct exposure to these

countries was already nil. This limits the possibility that their behavior was dictated by an effort to limit their exposure to emerging euro-area risks.

The model in section 2.3 abstracts, for simplicity, from various features of reality. In particular, it normalizes the speculators' maximum long position in the asset to 1. However, to test the main insights of the model I can extend its baseline version to allow for more flexibility, positing that the cap on speculators' asset holdings is $\bar{a}$, i.e. $a \in [0, \bar{a}]$. The results in Lemma 1 and 2 continue to hold because, at the margin, the speculators' decision is unaffected. However, as $\bar{a}$ increases the amplification effect on the asset price is stronger, because each speculator has a more significant impact on the price. The idea is to compare assets that have different levels of $\bar{a}$ and test if the assets with higher $\bar{a}$ are sold more than those with lower $\bar{a}$ during periods of high uncertainty.

In this vein, to gauge the importance of the strategic motive for the funds' behavior, I propose to exploit the empirically observed heterogeneity among issuers as a way to proxy for complementarity among funds. The idea is that since speculators' interest in sell to repurchase is greater if other speculators are expected to do the same in the near future, the degree of complementarity can be captured by the number of funds that each issuer is dealing with in the pre-period. In other words, each single fund is expected to have a stronger impact when fewer funds are trading the assets of a given issuer, i.e. higher $\bar{a}$. I compute the number of funds that invest in each single issuer in the pre-period and taking this as a measure of complementarity, I test the following hypothesis:

H. 1 *Issuers with fewer funding relationships should be more vulnerable to my mechanism: their assets should be more commonly sold and bought back; yields should increase while maturity should shorten after October, 2011.*

That is, Hypothesis 1 expresses the idea that funds have a stronger incentive to profit from fluctuations when strategic interaction among funds is stronger and each fund has a stronger impact on a given issuer funding opportunity. It follows from the complementarity among speculators highlighted in Proposition 7 and the time-series pattern described in Figure 1-4. The main challenge empirically is to isolate the speculative motive for funds' behavior from other potential sources of heterogeneity among issuers that might be captured by this measure

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of complementarity, such as unobserved heterogeneity in risk. Section 1.5 analyzes possible alternative mechanisms to explain the results.

Next, I exploit the cross-sectional variation across funds to identify those most likely to behave like the speculators in my model and take advantage of market turmoil. In particular, Hypothesis 2 follows from the "cashing-in" equilibrium and has implications for the funds' behavior over time:

H. 2 *Speculators, when faced with a future negative shock to the market that has little impact on the long-term value of their portfolios first trade in the direction of the shock and then buy the asset back.*

In the model, absent the uncertainty shock at time zero (i.e. $\varepsilon = 0$), speculators would behave in exactly the same way as long-term investors, namely buy as long as the asset's price is below the fundamental value. The empirical challenge, then, is to find a source of heterogeneity across funds that might induce some to take advantage of the fluctuations in the market. In Section 1.6 I show that funds' portfolio liquidity is a good proxy for incentives to do this. The idea is that funds that have a large part of their portfolio maturing soon will not be interested in exploiting the temporary mispricing, as they can just wait for the asset to mature to capture the final payoff. But a fund with a less liquid portfolio has a stronger incentive to rebalance, in order to take advantage of this period and I show that the less liquid funds are in fact the treatment group of interest.

Finally, if funds have a mainly strategic incentive to sell off assets and plan to pinpoint the time when the market bottoms out, we should find that they adjust their portfolios after the uncertainty shock of October 2011 in order to be able to get back into the market at the best time. The model developed in section 2.3 can capture this feature by allowing the speculators to affect their ability to trade the asset. In fact, suppose that speculators trading opportunities arrive at rate $\alpha\phi$, where $\phi \in \{0,1\}$, with $\phi = 1$ capturing a liquid portfolio and $\phi = 0$ an illiquid one. Speculators can increase their portfolio liquidity ϕ at $t = 0$ by paying a fixed cost ξ, which captures potential transaction costs or the forgone potential returns of investing in more illiquid securities. In this scenario, speculators can trade only if they have the opportunity (time T_α is realized) *and* they have a liquid portfolio ($\phi = 1$). In this version

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of the baseline model, speculators holding the asset would have an incentive to pay ξ only in a "cashing-in-on-the-crash" equilibrium. This observation suggests the following hypothesis:

H. 3 *Funds might strategically hoard liquidity to time the bottom of the market.*

Hypothesis 3 follows from the speculators' incentive to rush to the market, increasing the probability of trading, and when the uncertainty is resolved to realize higher capital gains. This hypothesis is also useful to disentangle the strategic motive from any precautionary motives.

1.4.3 The Institutional Setting: Money Market Funds

Money market funds are important intermediaries between investors who want low-risk, liquid investments and banks and corporations that have short-term borrowing needs. The funds are key buyers of short-term debt issued by banks and corporations: commercial paper, bank certificates and repurchase agreements with an aggregate volume of $1.8 trillion. Given the importance of short-term credit markets to both investors and businesses, any disruption represents a potential threat to financial stability. MMFs have recently drawn the attention of a strand of the literature exploring their behavior during the financial crisis in 2007-2009 (Kacperczyk and Schnabl (2012) and Gorton and Metrick (2012)) and the more recent Sovereign debt crisis (Chernenko and Sunderam (2012) and Ivashina et al. (2012)). I contribute to this literature by showing the impact of funds' trading strategies on financial institutions' funding opportunities and by highlighting the strategic motive behind MMFs' behavior.

In the United States money market funds' holdings are regulated by Rule 2a-7 of the Investment Company Act of 1940. The funds are prohibited from purchasing long-term assets such as mortgage-backed securities, corporate bonds, or equity and can only hold short-term assets; and even these short-term liabilities must be of high quality. As an additional requirement, to enhance diversification, the funds cannot hold more than 5% of their assets in the securities of any individual issuer with the highest rating and not more than 1% in the securities of any other issuer.

In January 2009, after a tumultuous year for money market funds, the SEC voted to amend the 2a-7 rules to strengthen money market funds. The new rules seek to limit the risk and on enhance fund disclosures. For instance, funds are now required to have enhanced reserves of

cash and readily liquidated securities to meet redemption requests, and they can invest only 3 percent (down from 5 percent) of total assets in tier-2 securities, the term on which is limited to a maximum maturity of 45 days.

Under the new rules, starting in November 2010 money market funds have make monthly disclosure of detailed data, including each fund's holdings and shadow net asset value (NAV). This information becomes available to the public after 60 days. The new N-MFP form on which it is filed constitutes the main source of data for the present study.

First let me consider the various money market instruments held by funds (data provided by the Investment Company Institute). I focus on taxable funds because non-taxable funds hold tax-exempt instruments issued by state and municipal governments, which are not the focus here. Taxable funds accounted for 89% of all money market funds' assets under management in 2011.

As of August 2011, there were 431 taxable money market funds, holding assets worth $2.69 trillion; $1.43 trillion, or 53.2% of total assets, was held by prime funds that invest in non-government assets. Among the prime funds, $887 billion was held by institutional funds and $546 billion by retail funds. The largest asset classes held by prime funds were commercial paper, accounting for $351 billion, or 24.6% of the total, and repurchase agreements ($185 billion or 13.1%). The securities had average maturity of 39 days.

The surge in market uncertainty in Europe, mostly associated with the sovereign credit risk of Greece, Spain, and Italy, raised concerns about the U.S. financial institutions' exposure to these countries. Furthermore, these institutions might have greater exposure to major financial institutions elsewhere in Europe that in turn have important ties and significant exposure to the countries at risk. For instance, money market funds provide substantial short-term funding to several major European banks as well as cash to the tri-party repurchase agreement market. At the beginning of my sample period, in August 2011, the funds' exposure to Europe accounted for 23% of their total assets, with 12% invested in the euro area and the remaining 11% in other EU countries. Funds' exposure to other regions includes Asia with 3.4% and Oceania with 2.8% of assets; the remainder was allocated to the Americas (mainly the US). At the end of the sample period in May 2012, the picture had changed somewhat, the funds having reduced their exposure to Europe to 18% of total assets and increased their investments in Asia and the

Americas.

1.4.4 Data and Summary Statistics

This study employs a novel dataset on the universe of taxable money market funds obtained from iMoneyNet, which covers the period from August 2011 to May 2012. The dataset includes monthly fund-level data on returns, expense ratios, type of investors, average portfolio maturity and, most important for my purposes, portfolio information on assets, such as the amount invested and the characteristics of the securities held. These data are then complemented by Datastream data on the one-year CDS premia for the European financial institutions and corporations in my sample.

Table 1.1 gives summary statistics for all taxable money market funds as of August 2011. The sample includes 340 funds with an average size of $6.9 billion. In terms of portfolio composition, the funds hold 15% of their assets in floating-rate notes, 24% in repurchase agreements, 6.4% in asset-backed commercial paper, 12.2% in bank obligations, 26% in U.S. Treasuries and agency-backed debt, and 2.1% in deposits.

The weighted average maturity of their assets is 34 days, and on average 54% matures within seven days. The average return of the funds is 25 basis points. I compute the annualized spread as difference between the fund's return (net of expenses) and the yield on three-month Treasury bills, which averaged 5 basis points in August 2011. The mean holding risk, defined as the fraction of resources invested in assets other than repos and Treasuries, is 70%.

Information on some issuer characteristics is also available. First, the commercial paper they issue and their repurchase agreements with the funds have an average maturity of 29 days, ranging from overnight repos to 350-day commercial paper. Second, the average yield on these assets is 36 basis points, but can be as high as 1% for some issuers. On average, the CDS of these issuers is 150, confirming that this is a low-risk market. Finally, the main source of heterogeneity among issuers is the number of relationships they have with the funds. On average each issuer sells its liabilities to 54 different funds, but some such as DZ Bank, deal with just few funds, while others, e.g. Deutsche Bank, deal with scores and scores.

1.4.5 Empirical Strategy and Main Results

The micro nature of the data is essential to my econometric identification of the impact of uncertainty on the MMFs incentives. This feature essentially enables me to exploit not just time-series but cross-sectional variation across issuers and funds to evaluate how the latter reallocate their investments when uncertainty spikes, separately from other possible confounding factors driving MMFs behavior.

In this section, I test the main mechanism of the model: speculators selling their holdings because they expect others to sell, and this allows them to capture higher capital gains by buying the asset back after the uncertainty is resolved. This mechanism implies that we should observe heterogeneity in the type of assets that are more and less likely to be subject to such behavior. In particular, the model predicts this mechanism to be stronger for the assets for which the complementarity among funds is stronger.

To measure complementarity among funds, I exploit the depth of my data, by constructing a variable, *Issuer Number Ties*, as the number of funds that are counterparts to the issuer in August 2011. The assumption is that more diversified issuers are less affected by the funds' incentive to maximize their capital gains, which in turn reduces the funds' ability to profit from selling the issuer's asset when uncertainty spikes. In other words, issuers that deal with fewer funds are more sensitive to the funds' trading decisions.

To see how funds responded to the increase in uncertainty in the European financial markets, I use a differences-in-differences regression model to estimate the differences between post-uncertainty shock and pre-uncertainty shock coefficients for funds asset holdings of issuers with different numbers of borrowing relationships. Formally, I restrict attention to holdings in the euro area and estimate the following regression model[30]

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \varepsilon_{i,t}, \tag{1.8}$$

where $\Delta Invested_{i,g,t}$ is the change in the fraction of assets under management, or the change in the amount invested by fund i at time t in the asset issued by institution g. I estimate (1.8) over

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[30] I have estimated the same regression model (1.8) using the whole dataset and focusing on the triple interaction between *Issuer Number Ties*, the *Post* indicator and a dummy variable equal to 1 for holdings in the euro area; the results were similar.

two sample periods. First, I estimate the effect of an uncertainty shock in the period August 2011-January 2012; in this case the *Post* variable is an indicator variable equal to 1 after October 2011. Second, to discover the funds' behavior when uncertainty dissipates, I estimate (1.8) for the period October 2011-May 2012; in this case the *Post* variable is an indicator variable equal to 1 after February, 2012. γ_t denotes time-fixed effects, but I also include issuer-fixed effects ϕ_g. Since the amount invested in issuer g is an issuer-specific attribute, I allow for arbitrary correlation over time and among observations for each issuer by clustering standard errors at the issuer level.[31] The coefficient we are interested in is β_1, which measures the differential impact of uncertainty on issuers with higher numbers of ties to funds (for which the strategic motive among funds is weaker) that are based in the euro area relative to that of the issuers with fewer relationships (for which the strategic motive among funds is stronger).

Columns (1) and (2) of Table 1.3 show the estimated coefficients for the first sample period. We see here that the coefficient of interest β_1 is positive and significant, even controlling for time and issuer-fixed effects. Intuitively, during this period the funds were diminishing their exposure to the euro area, but Columns (1) and (2) show that they tended to reduce their investment in the liabilities of issuers with fewer funding relationships, i.e. those for which the complementarity with other funds was stronger. The results are also economically significant: a one-standard-deviation decrease in the number of relationships would decrease the funds' exposure to these issuers by at least 12 basis points or $6 million, which corresponds to 63% of the cross-section standard deviation of the dependent variable.

Columns (3) and (4) show the estimated coefficients for the second sample period. The coefficient β_1 is negative and significant, meaning that once uncertainty vanishes the money market funds tend to increase their holdings, in particular, in the issuers with fewer funding relationships. These results confirm the time-series pattern highlighted in Proposition 7 and provide evidence for the idea that funds' behavior in periods of high-uncertainty might be explained by strategic interaction among funds.

A possible explanation for these results could be that issuers with different numbers of ties also differ in riskiness. The difference-in-difference procedure and the inclusion of issuer-

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[31] I also tried specifications clustering the standard errors at the fund level, but the standard errors were lower. Hence, I reported the most conservative ones.

fixed effects control for time-invariant issuers characteristics such as size and reputation; and time-fixed effects control for shocks common to all issuers. For instance, a larger institution is likely to deal with more money market funds to satisfy its short-term funding needs than a smaller one. However, these differences will affect the result only if they vary in the post period. I address this concern by including the issuers' CDS premia as a measure of the risk associated with buying that issuer's liabilities and its interaction with the *Post* indicator to capture variation in riskiness due to the shock in October 2011.

Table 1.4 shows the estimated coefficients of the following regression model for the two samples:

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \alpha_1 Issuer\ CDS_{g,t} + \alpha_2 Issuer\ CDS_{g,t} \times Post + \varepsilon_{i,t}$$

$$(1.9)$$

which is the same as in (1.8) except for the fact that now I control for the issuer CDS and its interaction with the two *Post* indicator variables for the two sample periods.

Columns (1) and (2) reveal two noteworthy findings. First, risk-related considerations are indeed important in explaining money market funds' behavior, especially in the post-uncertainty shock period, as is underscored by the significance at the 1% level of the coefficient α_2. Intuitively, when uncertainty spikes funds tend to disinvest more from the issuers whose riskiness has increased as a consequence. Second, the coefficient β_1, is still significant at the 1% level and is even larger. In fact, controlling for the change in the riskiness of the issuers, a one-standard-deviation decrease in the number of borrowing relationships of issuer g induces funds to decrease their exposure to these issuers by at least 28 basis points. This means that the heterogeneity in the number of funding relationships cannot be fully explained by heterogeneity in risk. Columns (3) and (4) show that this result also holds for the periods in which uncertainty ends: even controlling for changes in issuers' risk, funds liquidate more of the assets of the issuers with fewer relationships. So it can be concluded that even if issuer risk influences funds' decisions, including it as a control strengthens my results.

1.4.6 Consequences for Issuers

So far I have examined the funds' trading behavior in response to an increase in uncertainty. The question now is how their short-term borrowing are affected. In this section, I address this issue by analyzing the effect that the funds' trading behavior has on issuers, in particular, on the maturity and yields of the assets. If Hypothesis 1 is true and my proxy does capture an important source of variation across issuers, we should find that issuers with fewer funding relationships suffer more in situations like the recent European debt crisis.

I consider two natural proxies to measure how hard it is for issuers to get funding during my sample period: the maturity of their funding agreements and the yields they have to pay to compensate the MMFs. Intuitively, it might be harder for an issuer to obtain funding if he needs to borrow at shorter maturity, (say, overnight repos), and if the interest rate that he needs to pay is higher. Suggestive evidence that this is the case is provided by Figures 1-10 and 1-11, which show that the average maturity (yield) of the securities issued by European institutions decreased (increased) significantly more for those issuers with fewer funding relationships after October 2011.

To control for unobserved heterogeneity among issuers, Table 1.5 shows the results of the following regression model:

$$Issuer\ Maturity_{g,t} = \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \gamma_t + \phi_g + \varepsilon_{g,t}, \tag{1.10}$$

where the dependent variable is the average maturity of the assets sold by issuer g at time t. As in the previous regression model (1.8), I control for time- and issuer-fixed effects, to account for the effects of time-varying demands for short-term funding and for the differences in issuers' characteristics, such as size, creditworthiness and access to other forms of credit.

Column (1) indicates that from August 2011 to January 2012 the average maturity of these assets tended to decrease. This might be explained as an attempt by the funds to guard against the risks of a collapse of the euro area by lending at a shorter maturity. Columns (2) and (3) introduce the time- and issuer- fixed effects, respectively. Column (3) shows that a one-standard-deviation decrease in the number of ties reduces the average maturity of the assets by at least three days. This result is both statistically and economically significant, as the

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average maturity of the commercial paper and repos in this market is only about 30 days. In contrast, Columns (4)-(6) highlight that for the second sample period (October 2011-May 2012) the opposite is the case, as the average maturity increased for all the issuers but significantly less so for those with more borrowing relationships.

To determine whether issuers with different numbers of funding relationships behaved differently even in the absence of the uncertainty shock, Figure 1-12 depicts the time-series coefficients of the following regressions:

$$Issuer\ Maturity_{g,t} = \sum_{\tau \neq t_0} \beta_\tau Issuer\ Ties_{g,\ Aug\ 11} 1_{(\tau=t)} + \gamma_t + \phi_g + \varepsilon_{g,t},$$

where $1_{(\tau=t)}$ is a dummy variable equal to 1 for month t. I have normalized the coefficient $\beta_{Oct\ 11}$ corresponding to October 2011, to zero. This event study shows that in the pre-period there was no difference in asset maturity among issuers with different numbers of ties that might explain my results. In other words, the treatment group (issuers with fewer funding relationships) and control group (more funding relationships) were on parallel trends in the pre-period.

I now turn to the analysis of the impact of funds' trading behavior on the interest rates paid by the issuers for short-term funds. I estimate a regression similar to (1.5):

$$Issuer\ Yield_{g,t} = \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \gamma_t + \phi_g + \varepsilon_{g,t},$$

where the dependent variable is the average yield on the commercial paper issued by institution g at time t. As before, I control for time-fixed effects and issuer-fixed effects, so as to capture all of the time-invariant characteristics of the issuer that can affect their cost of capital.

Columns (1) and (2) of Table 1.6 show that after October 2011, yields rose for all issuers, as is shown by the positive and significant coefficient of the *Post* variable, but significantly less for those with more funding relationships. Specifically, a one-standard-deviation decrease in the number of funding relationships increases the yield by more than 3 basis points. This finding is both statistically and economically significant, as the mean of the dependent variable is 36 basis points. Columns (3) and (4) provide further support for my hypothesis, showing that when uncertainty fades the yields began decreasing but to a significantly lesser extent for the

issuer with more funding relationships.

As before, I conduct an event study to show that the yields of European institutions with different numbers of ties did not start to diverge until after the shock of October 2011. Formally, Figure 1-13 plots the time-series coefficients β of the following regression:

$$Issuer\ Yield_{g,t} = \sum_{\tau \neq t_0} \beta_\tau Issuer\ Ties_{g,\ Aug\ 11} \mathbf{1}_{(\tau=t)} + \gamma_t + \phi_g + \varepsilon_{g,t},$$

where, as before, I normalize the coefficient $\beta_{Oct\ 11}$ to zero. Figure 1-13 shows that only after the shock of October 2011 did the issuers with fewer relationships have to pay higher rates to meet their short-term borrowing needs.

In summary, I have shown that when an uncertainty shock occurs, funds disinvest more from issuers with few relationships with other funds, i.e. those for which complementarity among funds is stronger. The opposite holds when uncertainty ends. Moreover, this trading strategy is costly for issuers: it reduces the average maturity of their liabilities to the funds and increases the interest rate that they must pay. These results confirm that issuers with fewer funding relationships tended to suffer the most during the recent European debt crisis: their cost of capital increased and their balance sheets were adversely affected as they were obliged to borrow at shorter maturities, heightening rollover risk. These results indicate how MMFs may have amplified the impact of negative shocks by squeezing European financial institutions' positions and funding.

1.5   Alternative Explanations

In this section, I explore three alternative mechanisms to explain the results shown above and I provide evidence that the strategic motive for MMFs' behavior can be disentangled from other motives.

1.5.1   Fund Distress

The financial crisis highlighted the potential risks associated with money market funds. On September 16, 2008, because of its exposure to Lehman Brothers' debt securities, the Reserve Primary Fund "broke the buck". It entered into a prolonged liquidation process, ultimately

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leading to its closure. This event had broad repercussions, as investors began withdrawing their money from other MMFs, fearing that they too might be exposed to Lehman or to other issuers at heightened risk of default or market-value decline. These events suggest that one important motive driving funds' behavior is to avoid a distressed situation that might require support from the fund sponsor or drive them to "break the buck". This could be a problem for my identification strategy if funds liquidate the assets of issuers that are less widely held by other MMFs during periods of distress, which might be captured by an increase in uncertainty.

Then, in this section I investigate the possibility that the results shown in Tables 1.3 and 1.4 may be explained by heterogeneity in funds' financial health. The approach to identifying this mechanism is threefold. First, I have data on the funds' net assets value (NAV), excluding sponsor support. In response to the Reserve Fund collapse, the SEC mandated that funds disclose their NAV every month, net of cash transfers from or asset purchases by the sponsoring institution. To estimate the effect of this "financial distress" motive, I define the variable *Break the Buck*$_{i,t}$ as $1 - NAV_{i,t}$ for each fund i at time t; higher values indicate a greater probability of distress. The regression model estimated is a modification of (1.8)

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \alpha_1 Break\ the\ Buck_{i,t} + \alpha_2 Break\ the\ Buck_{i,t} \times Post + \varepsilon_{i,t}$$

$$(1.11)$$

where the coefficient α_2 embodies the hypothesis that funds' trading strategy is driven by the greater probability of market decline when uncertainty increases. Column (1) of Table 1.7 shows the results after controlling for this measure of distress: the results are totally unaffected by the inclusion of this additional control.

Second, I estimate (1.8) and exclude the funds with a NAV below 1, approximately 20% of my sample. Column (2) of Table 1.7 demonstrates that the coefficient β_1 is still significant at the 1% level and is of the same magnitude as before.

Finally, I exclude the funds that received support from their sponsoring institutions in 2010 and 2011. The idea is to rule out the possibility that my results might be driven by these funds liquidating their holdings in smaller institutions in order to buoy their financial resilience. These funds can be identified thanks to a recent study by Brady et al. (2012) which reviews the public

MMFs' annual SEC financial statement filings (form N-CSR) and identifies those that would have broken the buck between 2007 and 2011 in the absence of sponsor support. My sample includes 11 of these funds. Column (3) shows the estimated coefficients from (1.11) excluding them; the previous findings again stand confirmed.

In summary, the evidence is that the heterogeneity of trading patterns across issuers cannot be explained by funds' fear of possible distress should the assets of the less widely held issuers lose value.

1.5.2 Diversification Motive

The Federal Reserve responded to the financial crisis with several unconventional interventions to curb investors panic. For instance, on September 22, 2008, following the collapse of Lehman Brothers, the Fed introduced the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF). The AMLF was the primary tool to provide a liquidity backstop for MMFs, which were experiencing a run. It provided a means for money market funds to liquidate assets, but not at fire sale prices, in order to meet investors' demand for redemptions, thus preventing many MMFs from "breaking the buck."[32]

This response suggests that now, the money market funds could well expect the Fed to step in at times of increased uncertainty, especially when the very functioning of the money markets is at risk. But this might not be true if only a single fund were in distress. These observations point to the possibility that funds' behavior in periods of high uncertainty may be dictated by the desire to liquidate positions that expose them to idiosyncratic risk, including for instance, the holdings of smaller institutions that are not widely held. This source of heterogeneity across issuers, generated by the implicit government-put protection, is not captured by CDS premia and must be accounted for separately. In particular, if the uncertainty shock heightens the default risk of Deutsche Bank because of its holdings of Greek bonds, its CDS premia will increase. But money market funds might still prefer to continue holding Deutsche Bank commercial paper, because in the case of default, it is reasonable to expect the Fed to intervene, as most of the funds would be in distress. The opposite might be true for DZ Bank: its perceived

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[32] Duygan-Bump et al. (2012) analyze the effectiveness of this intervention in detail.

risk may be relatively less affected by the uncertainty shock in October 2011 but the funds liquidate its assets because only a few are exposed to its default risk.

My approach to disentangle the strategic motive from this alternative mechanism is three-fold. First, I estimate (1.9) both for the funds with below-average and above-average exposure to the euro area. The idea is that funds are more likely to liquidate their holdings of institutions with fewer funding relationships if they already have high exposure to the euro area. Columns (1) and (2) of Table 1.8 show the results for the funds with low exposure, Columns (3) and (4) those for the funds with high exposure. In Columns (1) and (3) the dependent variable is the change in the fraction of assets under management invested in the assets of issuer g, while Columns (2) and (4) consider the effect on the amount invested. The effect of the number of ties is still positive and significant in Columns (1), (3) and (4). The lack of significance in Column (3) can be explained by the reduced number of observations. The magnitude of the effect is greater for the funds with below-average exposure to the euro area, as highlighted by the comparison of Columns (1) and (3). This finding suggests that my main results cannot be explained by a desire to diversify across regions.

Second, I include the number of different European issuers that are held in the fund's portfolio in the regression. The idea is that a fund that has invested in very few European issuers might be extremely susceptible to changes in the market value of these securities and might behave differently from a fund with better diversified portfolio. Column (5) shows that more diversified funds tend to increase their exposure to these European issuers. However, the coefficient β_1 is still positive and significant, and its magnitude is comparable to that found in Table 1.4. This shows that while portfolio diversification may be important, it cannot explain the funds' trading strategy of selling more of the assets of issuers with fewer borrowing relationships.

Finally, I define *Fund Share Issuance$_{g,i,t}$* as the share of the total dollar amount of assets sold by issuer g at t that is held by fund i. The idea is to capture the possibility that a fund might be more worried about the default of issuer g if it holds a larger portion of issuer g's liabilities. Column (6) investigates this possibility by including *Fund Share Issuance$_{g,i,t}$* as an additional control variable. Again, the results are not affected.

In summary, diversification motives across funds, especially in light of a potential inter-

vention by the Federal Reserve, might be important but do not explain why funds tend more strongly to sell the securities of the issuers with fewer funding relationships more often.

1.5.3 Differences in Market Liquidity

Brunnermeier (2009) reports that liquidity completely evaporated in many financial market sectors during the financial crisis of 2007-09; some markets, such as the ABS market, simply froze up.[33] This observation suggests that the liquidity of short-term debt securities could be a prime concern for MMFs. Funds might try to sell the positions that they expect will be harder to liquidate in the future if economic conditions deteriorate further.

My identification strategy takes account of unobserved differences across issuers and across markets, with the inclusion of issuer-fixed effects. But this identification would fail if the rise in uncertainty in October 2011 had differing impact on the liquidity of the markets and if this were correlated with issuers' number of funding relationships. For instance, liquidity, defined as ease of selling, might vary across assets of different issuers, and one presumes that those of widely-held issuers are easier to sell, as there are far more potential buyers. This would not be a problem if it were a fixed characteristic of the issuers' securities, but it could affect my estimates if the uncertainty shock affected the funds' opportunity to sell their assets differently.

I measure liquidity in three alternative ways. I observe the maturity and yields of the assets of different issuers. The idea is that an asset of longer maturity is harder to sell at a fair price (Edwards et al. (2007) and Bao et al. (2011)). Similarly, the liquidation risk is partly reflected in the yields that funds require to hold the assets. So on this logic, as an additional control I include in my main regressions the average maturity and yield of the assets issued by institution g (result in Column (1) of Table 1.9). These have no effect on the main coefficient of interest.

Column (2) also includes the interaction terms between these measures of liquidity and the post-indicator variable, to allow for the possibility that the variation in market liquidity as a result of the spike in uncertainty is what is captured by the number of ties. Column (2) shows that this is not the case. In fact, the effect of the number of funding relationships is still positive and significant at the 1% level.

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[33]Brunnermeier and Pedersen (2009) analyzes the connection between market liquidity (ease with which one can raise money by selling an asset) and funding liquidity (ease with which one can raise money by borrowing using the asset as collateral) and the possibility that they reinforce each other.

Finally, it is reasonable to suppose that funds have different liquidity constraints depending on the supply of the assets of issuer g. In principle this could work in two directions. On the one hand, issuers that have pumped a larger amount of securities into the market might have a harder time finding a new buyer that is willing to absorb their assets. On the other hand, bigger issuances are likely widely held across MMFs, which means that it might be easier to liquidate these positions as necessary. For this reason, in column (3), I control also for the total dollar amount of the outstanding assets of issuer g at time t and for its interaction with the post indicator. The results are even stronger than before, as the magnitude of the coefficient increases.

In summary, my results are robust to the inclusion of several proxies for market liquidity.

1.6   Who are the Speculators?

This section investigates which types of funds are more likely to exploit increased uncertainty, with evidence in support of Hypotheses 2 and 3. The hypothesis suggested by the model is that the funds that are more prone to sell their holdings when uncertainty spikes are those most affected by short-term fluctuations. This suggests that the incentives to capture capital gains are greater if the fund's portfolio has longer maturity, which will allow it to profit from price swings. The idea is: a fund that has 80% of its assets maturing within seven days has less incentive than one that has only 30% maturing. In fact, the latter is affected more severely by the negative shock and may opt to liquidate some of its holdings early in order to buy them back at a better price.

The foregoing suggests that the fraction of assets maturing within seven days might be a good proxy for the fund's incentive to take advantage of market fluctuations. This is highlighted in Table 1.2, which shows the summary statistics for the main fund characteristics for short-maturity and longer-maturity funds. The latter are usually larger in terms of AUM and invest more in riskier asset classes, ABCP, bank obligations (both domestic and foreign banks) and significantly less in U.S. treasuries and repos. Moreover, funds with less liquid portfolios are more likely to be institutional than retail funds. This finding suggests that the funds with less liquid portfolios are more sophisticated than those with more liquid portfolios and so can play

the role of speculators in this market.

Next, I divide MMFs into two groups according to portfolio liquidity. The primary measure of portfolio liquidity is the fraction of their portfolio maturing within seven days. High-liquidity funds are those above the median in this indicator, low-liquidity funds are those below the median. Figure 1-14 shows the kernel distribution of liquidity across funds as in August 2011. There is significant variation across funds, ranging from 10% to almost 90%. Figure 1-15 gives the time-series exposure of MMFs to the euro area, showing that after the October 2011 shock the less liquid funds do indeed liquidate more of their European assets and then reenter the market more aggressively after February 2012. This finding suggests that the liquidity of the funds' portfolio does capture an important source of variation that might explain their trading behavior.

To exploit this cross-sectional variation across funds while controlling for other sources of unobserved heterogeneity, I estimate the following difference-in-difference regression model for differences between the post- and pre-period coefficients:

$$Euro\ Exposure_{i,t} = \gamma_t + \eta_i + \beta_1 Post_{Oct\ 2011} \times Liquidity_{i,Aug\ 2011} + \delta \mathbf{X}_{i,Aug\ 2011} + \varepsilon_{i,t}, \quad (1.12)$$

where $Euro\ Exposure_{i,t}$ is the main dependent variable and is defined as the fraction of assets invested in the euro area by fund i in month t, η_i denotes fund-fixed effects, and γ_t denotes time-fixed effects. $Post_t$ is an indicator variable equal to 1 after October 2011, which identifies the high-uncertainty period. $Liquidity_{i,Aug\ 11}$ is the fraction of assets maturing within seven days, as of August 2011. When I do not control for fund-fixed effects, I include $\mathbf{X}_{i,Aug\ 2011}$, a vector of fund-specific controls that includes size, average annualized gross 7-day yield, and the fraction of assets invested in repos, U.S. Treasury securities and foreign bank securities. These variables control for the observed differences across funds, which might be correlated with their behavior in the post period. Both the liquidity variable and the other controls are measured as of August 2011, which mitigates any concern that investment choices are driven by changes in fund characteristics because of variations in uncertainty in the post-period. Since the exposure to the euro area is a fund-specific attribute, it is possible that it is serially correlated. To

address this concern, I cluster standard errors at the fund level. The coefficient of interest is β_1, which measures the differential impact of uncertainty on the more liquid funds' exposure to the euro area relative to that of the less liquid ones.

I begin with a nonparametric analysis of the observed effects. For each month between August 2011 and May 2012, I estimate the coefficient from the cross-sectional regression model (1.12) for Liquidity. Specifically, Figure 1-16 presents the coefficients β_τ of the following regression model

$$Euro\ Exposure_{i,t} = \sum_{\tau \neq t_0} \beta_\tau Liquidity_{i,Aug\ 11} 1_{(\tau=t)} + \gamma_t + \eta_i + \varepsilon_{i,t},$$

where I have normalized the coefficient for October 2011 to zero. I find no visible differences in the impact of uncertainty prior to October 2011 on exposure to the euro area, but starting at that date there is a large positive effect of Liquidity. This finding validates my econometric approach by showing that the pre-trends between the treatment group (low-liquidity funds) and control group (high-liquidity funds) are indeed parallel. In other words, funds might have very different levels of exposure to the euro area, but their trends are not significantly different in the period preceding the spike in uncertainty. This parallels what happens in the model when $\varepsilon = 0$: the speculators behave exactly like the buy-and-hold investors.

Furthermore, Figure 1-16 also shows the dynamics of the effect: increasing right after the shock in October 2011 and then decreasing in the second quarter of 2012. Funds react to the new high-uncertainty environment for a fairly extended period of time, between three and four months. This could reflect the fact that while some assets can be readily liquidated, such as overnight repos, others such as commercial paper take longer.

Next, I present the results of the difference-in-difference regression corresponding to the nonparametric analysis. Column (1) of Table 1.10 confirms that in the post-period, funds decreased their exposure to the euro area significantly, by more than 4 percentage points, as is shown by the significance of the Post variable. Moreover, more liquid funds decrease their exposure less than the less liquid ones. The results might be driven by other shocks or news released after October 2011, and to address this question I include time-fixed effects in columns (2)-(6). The results might also be driven by unobserved time-invariant differences among funds that are

correlated with liquidity. This issue is addressed by including fund-fixed effects in columns (3)-(6). In all of these specifications, no difference in the quality of the results emerges.

Column (3) of Table 1.10 shows the results for the baseline model. For the post-period, I find that a one-standard-deviation increase in *Liquidity* increases *Euro Exposure* by 89 basis points. These results are statistically significant at the 1% level. They are also economically significant: a one-standard-deviation increase in Liquidity corresponds to a 10% increase in *Euro Exposure* relative to the cross-sectional standard deviation of fund's *Euro Exposure*.

My effects might be driven not by differences in fund liquidity but by unobserved differences in investment styles, expertise or ability, which in turn might be correlated with liquidity. To the extent that the variation in style or risk aversion among funds is permanent, it would be accounted for by the difference-in-differences estimator. But the empirical approach taken here might fail if the variation affects risk-taking differentially in the pre and post periods. For example, funds may differ in their reactions to changes in uncertainty or in their propensity to take on risk when uncertainty arises.

My method of accounting for this possibility is twofold. First, I include a set of controls that might drive the results and capture (at least partially) heterogeneity across funds. These controls involve a set of fund and portfolio characteristics. The fund characteristics are yield, size, an indicator variable for institutional fund, weighted average portfolio maturity, pre-shock exposure to the euro area, and net asset flow. For instance, large funds are often thought to be more involved in active risk choices, while smaller funds are often considered simple, cash-parking vehicles with no active risk-management strategy. Or funds' behavior might be driven, at least partially, by redemptions; to account for this possibility, I control for the fund's net flow. Portfolio characteristics controlled for are the fractions of assets invested in foreign bank obligations, repos, ABCP and Treasuries. I include these time-varying characteristics, as measured in August 2011, in Column (2), and also in Columns (4)-(6). Second, in Column (6) I include fund-specific linear trends to check whether allowing for differential trends significantly changes the results in a meaningful way. It does not, further confirming the empirical strategy.

If uncertainty is the main driver of funds' decisions to lend to financial institutions and corporations in the euro area over the short term, the opposite effect should be true when the uncertainty regarding the European debt crisis is attenuated and the funds regain confidence.

Accordingly, I investigate whether money market funds resumed euro area asset purchases once uncertainty began to abate in February 2012 or whether they continued to invest exclusively in safe havens such as U.S. Treasury paper. Specifically, I estimate the following regression model, which is the counterpart to 1.12:

$$Euro\ Exposure_{i,t} = \gamma_t + \eta_i + \beta Post_{Feb\ 2012} \times Liquidity_{i,Aug\ 2011} + \varepsilon_{i,t},$$

where the dependent variable is also the fund's exposure to the euro area and $Post_t^{Low}$ is a dummy variable equal to 1 after February 2012, when the VIX began to decline significantly, mainly because of the strong intervention by the European Central Bank. In fact, the ECB launched a new form of "emergency relief", Longer Term Refinancing Operations (LTRO), which gave "breathing room" to banks struggling to find private sources of funding with a three-year lending facility, with a total of more than \$1.3 trillion borrowed.

Table 1.11 shows that β_1 is indeed positive and significant, suggesting an increase of 1.4% in exposure to the euro area after February 2012, which confirms the perceived normalization of the European situation. Moreover, the coefficient of interest, β_1, is negative and significant. This finding suggests that low-liquidity funds increase their holdings in the euro area as uncertainty fades, corresponding to what happens after T_ρ in the model.

These results confirm Hypothesis 2: speculators, when faced with a future market shock, first trade in the direction of the shock and then, when the uncertainty dissipates, buy the asset back.

1.6.1 Timing the Market

For additional confirmation of a strategic motive, I analyze how the funds changed their port-folios after the shock in October 2011. Specifically, if the funds temporarily reduced their exposure to the euro area and in particular to issuers with fewer funding relationships only temporarily, and then bought back at better terms, I should find that they had prepared by determining precisely the right moment to repurchase. In other words, the funds that want to maximize capital gains should become more liquid to be able to buy back as soon as the

uncertainty is dissipated. Formally, I estimate the following regression

$$Liquidity_{i,t} = \gamma_t + \eta_i + \beta Post_{Oct\ 2011} \times Liquidity_{i,Aug\ 2011} + \varepsilon_{i,t}$$

where the dependent variable $Liquidity_{i,t}$ is the fraction of fund $i's$ asset maturing within seven days. I control for fund- and time-fixed effects and cluster the standard errors at fund level. Table 1.12 shows that the funds that were less liquid in the pre-period acted like the speculators of my model did in fact begin to increase the liquidity of their portfolio after the October 2011 shock. This confirms Hypothesis 3.

1.7 Additional Empirical Implications

My theory yields a wealth of empirical implications in addition to those I tested in the previous section. I now discuss some of them in light of recent empirical evidence on the role of institutional investors during the recent financial crisis.

Prediction 1 *Liquidity tends to evaporate abruptly when uncertainty increases. And in such periods the returns to liquidity provision increase.*

Prediction 2 *All else equal, speculators are more likely to amplify fluctuations when the expected future shock is large, more likely and nearer in time.*

Prediction 3 *All else equal, speculators are more likely to amplify fluctuations in a bull than in a bear market; or equivalently, when they are initially more highly exposed.*

Prediction 4 *All else equal, speculators are more likely to amplify negative shocks in markets for less liquid assets.*

The evaporation of liquidity (Prediction 1) follows from the "cashing-in" equilibrium of Proposition 8 and is a consequence of the coordinated trading behavior of the speculators highlighted in Proposition 7. The sudden increase in the returns to liquidity-provision, instead, follows from the fact that the fundamental value of the asset is unaffected while its price is driven down by speculation. The sudden evaporation of liquidity was observed in many sectors of financial markets in 2007-09. Gorton and Metrick (2009) proposes the explanation

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that the crisis amplified asymmetric information problems: that is, several debt instruments became more information-sensitive, which aggravated adverse-selection problems. I propose an alternative, complementary hypothesis: speculators amplified the initial uncertainty shock by reducing liquidity supply because they forecast further shocks and sought to take advantage of them.

Nagel (2011) provides evidence consistent with Prediction 1, finding that during the recent crisis, the returns to liquidity-provision increased significantly and were closely correlated with the VIX index. Most likely, the VIX proxies for the underlying state variables that drive willingness to provide liquidity and the market's demand for liquidity. Nagel (2011) decomposes the VIX into conditional volatility and a volatility risk premium and shows that both components predict reversal strategy returns, with conditional volatility performing somewhat better. Moreover, several proxies for liquidity supply factors predict positive returns to the reversal strategy. This seems to confirm that what matters is not only news on fundamentals, which could have increased the adverse selection in financial markets, but that some potential arbitrageurs deliberately sought to profit from the potential crash.

Prediction 2 follows from speculators' trade-off between asset cash-flow and capital gains and is discussed in section 1.3.3. The trading behavior hypothesized seems to be confirmed empirically by Ellul et al. (2012). During episodes of market turmoil – dating back to the 1987 market crash, – Ellul et al. (2012) show that investors with short horizons (as proxied by portfolio turnover) sell their stock holdings to a larger extent than those with longer trading horizons. This creates price pressure on the stocks mostly held by short-horizon investors, which therefore experience larger price drops and sharper reversals than stocks mostly held by long-horizon investors. The evidence indicates that investors with short horizons amplify the effects of negative market-wide shocks, as the model predicts, by demanding liquidity when other potential buyers' capital is scarce. And these effects are larger when the expected shock, or market uncertainty, is greater (as captured by the comparison between the "black Monday" crash of 1987 and the Lehman Brothers' collapse in 2008).

My results concerning the role of speculators in stabilizing financial markets related more broadly to a strand of the literature that explores institutional investors' behavior during financial crises. Ben-David et al. (2012), for instance, show that, only part of hedge funds'

substantial reduction of equity holdings during the crisis in 2008 is explained by the need to meet redemptions.[34] This empirical finding suggests the possibility that at least a fraction of the liquidation is driven by strategic motives.

Confirmation of my mechanism, which relies on the interaction between speculators and long-term investors, comes from the evidence in He et al. (2010). They show that while hedge funds were deleveraging as the financial turbulence mounted, commercial banks significantly increased their asset holdings, absorbing the excess supply generated by the funds' sales. This suggests that in that context the role of long-term investors posited in my model is played by the commercial banking sector.

Prediction 3 follows from the Property 3 of the equilibrium presented in Proposition 13, whereas Prediction 4 follows from the comparative statics results presented in Proposition 10. These predictions suggest that the characteristics of the markets play an important if somewhat surprising role in shaping speculators' incentives. In particular, Prediction 3 posits that amplification of market shock is more likely when the market has just gone through a bout of euphoria, driving prices up. This resembles the mechanism proposed by Brunnermeier et al. (2008) in the analysis of carry trades in exchange markets. Uncertainty shocks have a more severe effect on speculators' incentives to hold an asset when in the aggregate they are more exposed to it. In the model, this corresponds to the fact that since more speculators are holding the asset at $t = 0$ and are not able to liquidate instantaneously due to trading friction, it will take time before they have sold all their holdings. This increases the expected capital gains to speculators from continuing to trade in the same direction as the shock.

Furthermore, Prediction 4 suggests that market illiquidity can be aggravated by speculators' behavior: their incentives to liquidate in the drive for the potential capital gains are greater in illiquid markets. This suggests that the mechanism hypothesized here should be more relevant in less liquid markets, such as those in which long-term investors are reluctant to further absorb excess asset supply without significant price concessions. Suggestive empirical evidence is provided by Manconi et al. (2012), who show that the investors more exposed to securitized bonds that fell sharply in price, sold more bonds and contributed to the price downswing.

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[34]Boyson et al. (2011) have analyzed similar data, but with a smaller set of hedge funds; they confirm that during the recent crisis hedge funds sold more equity holdings than required merely to face redemptions.

Consistent with Prediction 4, they find that the investors who expect liquidity shocks retain liquid assets and sell those that have relatively high temporary price impact.

1.8 Conclusion

I propose a model with long-term investors and speculators, who both participate in a market characterized by trading friction, and test its main predictions using a novel dataset on money market funds. I make three main contributions.

First, during periods of market turmoil and even though the long-term value of the asset remains unchanged, speculators react to declining asset prices by liquidating asset holdings, thus amplifying price fluctuations. The key idea is that speculators forgo dividends for capital gains, hoping to buy the asset back more cheaply after further turmoil. Importantly, the magnitude of the capital gains increases if other speculators are expected to follow similar strategies in the future. This finding suggests a strong role for complementarity in amplifying negative shocks. Moreover, I show that less trading friction is associated with sharper asset price decline and faster recovery after the shock occurs.

Second, I provide a framework for formal analysis of the link between periods of high uncertainty and the fragility of financial markets. I show that small shifts in investors' perception of the severity of future negative shocks might have discontinuous effects.

The main insights can be applied to other matters, such as the behavior of high-frequency traders or the dynamics of housing prices. The shocks posited, in fact, do not need to be macroeconomic shocks but could come at much higher frequencies. So the insights may contribute to the debate on high-frequency trading, which has been blamed for price volatility and extreme market swings, such as the May 2010 *flash crash*, when stock prices plunged hundreds of points before recovering. In the words of SEC Chair Mary Schapiro: "High-frequency trading firms have a tremendous capacity to affect the stability and integrity of the equity markets. Currently, however, they are subject to very little in the way of obligations [...] to refrain from exacerbating price volatility."[35] Regulators in the U.S. and Europe have recently proposed of a tax on financial transactions.[36]

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[35] "Remarks Before the Security Traders Association" (September 22, 2010).

[36] For instance, on December 3, 2009, a "Let Wall Street Pay for the Restoration of Main Street Bill" was

This paper's contribution to the debate is twofold. First, it formally demonstrates a mechanism by which high-frequency traders can destabilize financial markets. Second, it examines the way in which a transaction cost like the Tobin tax can affect trading strategies. I show that such tax could be a double-edged sword: it does mitigate the repercussions of increased uncertainty on investors' incentives to exploit small price movements; but by decreasing the liquidity of the market it might have a destabilizing effect, by encouraging funds' strategic behavior.

Given the central role that the housing market played in triggering the crisis, it is important to understand the determinants of house price dynamics over the recent cycle, as this would inform efforts to enhance financial stability. Recent papers by Haughwout et al. (2011) and Bayer et al. (2011) provide evidence that my mechanism fits this market, where trading friction is significant. Haughwout et al. (2011) identify real-estate investors (as opposed to owner-occupants) as a key factor in the house price surge and crash. They show that at the peak in 2006, in the four states with the most pronounced housing cycles, the investor share was 45 percent. In a similar vein, Bayer et al. (2011) analyze transaction data in the Los Angeles metropolitan area and identify intermediaries that attempt to time the market, showing that their presence is strongly associated with price instability. They argue that both the boom and the bust were driven by these investors or intermediaries (the speculators in my model), who had a much shorter trading horizon than owner-occupants (long-term investors).

My main result suggests that when house prices turned down in 2006, real-estate investors did not know whether the decline was temporary or the start of the bust: uncertainty about future prices increased. In light of my analysis, real-estate investors might have reacted to the heightened uncertainty by selling, provoking a more severe bust in the states where these investors were significant participants.

The third contribution of the paper lies in the empirical analysis of the importance of the mechanism revealed by the model, tested on a novel dataset on MMFs' portfolio holdings during the European debt crisis. I gauge the strength of strategic interactions among funds as the number of funding relationships that each issuer has with money market funds. I show that funds are much more likely to liquidate the assets of issuers that have fewer funding relationships. In

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introduced in the House of Representatives to levy a tax on securities transactions. Similarly, in September 2011 the European Commission proposed to institute a financial transaction tax in the 27 EU member states by 2014.

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other words, price destabilization is greater for assets characterized by greater complementarity among funds. As a result, the maturity of these issuers' assets shortens significantly and yields increase during high-uncertainty periods. These results are robust to alternative explanations based on precautionary or diversification motives for selling and on capital constraints.

These results have important implications for the debate on systemic risk. In fact, the strategic motive of the money market funds is one mechanism by which they could be endogenously correlated, exposed to the same source of distress: namely, the attempt to time the bottom of the market. This carries two important consequences: first, trading strategies impact on the balance sheets of other key institutions, such as commercial banks; and second, by selling the securities of the issuers with fewer funding relationships, they cause the other funds that deal with those issuers to fear a short-term loss in asset value, hence heightening the incentive to behave in the same way and sell as the price falls. My empirical evidence suggests that the trouble that so many European financial institutions and corporations had in obtaining short-term funding during the financial crisis and European sovereign debt crisis may not actually have been driven by the fundamentals. Instead, it could have been the result of money market funds' exploitation of the market turmoil. One implication is that the financial authorities, such as the SEC and Fed, should collect data on the prices at which these funds transact, in order to determine which funds have the most incentive to behave as speculators.

Several extensions would be worth exploring, two in particular. First, by allowing for asymmetric information among speculators, one could endogenize market depth and study the joint dynamics of liquidity and price. Second, one could allow for the arrival of news over time (concerning, say, the severity of future shocks) and study the impact of endogenous information flows on the price dynamics. I leave these extensions to future research.

1.9 Appendix A – Proofs

Proof of Lemma 1.

I can rewrite the value function (1.3) as

$$V\left(a,t\right)=\mathbb{E}_t[\int_t^{T_\alpha}e^{-r(s-t)}\delta ads+e^{-r(T_\alpha-t)}\left\{p\left(T_\alpha\right)a+\max_{a'}V\left(a\prime,T_\alpha\right)-p\left(T_\alpha\right)a\prime\right\}],$$

then subtracting $p\left(t\right)a$ and ignoring the terms that do not depend on a the problem of a speculator who gains access to the market at time t is given by

$$\max_{a'\geq 0}\int_t^{T_\alpha}e^{-r(s-t)}\delta a'ds-\left\{p\left(t\right)-\mathbb{E}\left[e^{-r(T_\alpha-t)}p\left(T_\alpha\right)\right]\right\}a'. \tag{1.13}$$

The speculator chooses his asset holdings in order to maximize the expected present discounted value of his utility flow net of the expected present discounted value of the cost of holding the asset from time t until the next time T_α, when he can readjust his holdings. Then, I compute the first term of (1.13) as

$$u\left(a\right)=\mathbb{E}\left[\int_0^{T_\alpha-t}e^{-rs}\delta ads\right]=a\frac{\delta}{r+\alpha}, \tag{1.14}$$

where the expectation is over the random variable $T_\alpha-t$. The expected discounted price of the asset at the next time when the speculator gets an opportunity to trade can be written as

$$\mathbb{E}\left[e^{-r(T_\alpha-t)}p\left(T_\alpha\right)\right]=\alpha\int_0^\infty e^{-(r+\alpha)s}p\left(t+s\right)ds. \tag{1.15}$$

Substitute (1.14) and (1.15) into (1.13) to obtain the formulation of the speculator's problem in the statement of the lemma. ∎

Proof of Lemma 2.

I can follow the same steps as in Lemma 1 to simplify the speculators' problem at $t < T_\rho$. I first compute the expected utility flows that the speculator experiences by holding portfolio a. Since the trading opportunities and the arrival of the shock follow independent Poisson processes, $T_\alpha - t$, and $T_\rho - t$ are exponentially distributed random variables with means $1/\alpha$,

and $1/\rho$, respectively. Define $T_{\alpha\rho} = \min\{T_\alpha, T_\rho\}$. Then, the utility flows is

$$
\begin{aligned}
u^U(a) &= \mathbb{E}\left[\int_0^{T_{\alpha\rho}-t} e^{-rs}\delta a^U ds\right] = \mathbb{E}\int_0^\infty \left[\int_0^{T_{\alpha\rho}} e^{-rs}\delta a^U ds\right](\alpha+\rho)e^{-(\alpha+\rho)\tau_{\alpha\rho}}d\tau_{\alpha\rho} \\
&= a^U\left(\frac{\delta}{r+\alpha+\rho}\right)
\end{aligned}
$$

One sees that this is exactly the same equation as in Lemma 1, except that now α is replaced by $\alpha + \rho$, which takes into account the possibility to enter the after-shock phase.

To derive the expected value of the price, I use the fact that $T_\alpha - t$ and $T_\rho - t$ are two independent exponentially distributed random variables:

$$
\begin{aligned}
&\mathbb{E}\left[e^{-r(T_\alpha-t)}(\mathbb{I}_{\{T_\alpha<T_\rho\}}p^U(T_\alpha) + \mathbb{I}_{\{T_\alpha>T_\rho\}}p^U(T_\alpha|T_\rho))\right] \\
&= \int_t^\infty \int_t^\infty e^{-r(\tau_\alpha-t)}(\mathbb{I}_{\{\tau_\alpha<\tau_\rho\}}p^U(\tau_\alpha) + \mathbb{I}_{\{\tau_\alpha>\tau_\rho\}}p^U(\tau_\alpha|\tau_\rho))\alpha e^{-\alpha(\tau_\alpha-t)}\rho e^{-\rho(\tau_\rho-t)}d\tau_\rho d\tau_\alpha \\
&= \int_t^\infty e^{-r(\tau_\alpha-t)}\left[e^{-\rho(\tau_\alpha-t)}p^U(\tau_\alpha) + \int_t^{\tau_\alpha}\rho e^{-\rho(\tau_\rho-t)}p^U(\tau_\alpha|\tau_\rho)\right]\alpha e^{-\alpha(\tau_\alpha-t)}d\tau_\rho d\tau_\alpha
\end{aligned}
$$

this completes the proof of lemma 2. $\blacksquare$

Proof of Proposition 3.

Given the results of Lemma 1 and 2 I can compute the optimal trading decision for a speculator who has the opportunity to submit his orders at time t. Let me start with $t > T_\rho$, there are two cases. First, the shock did not occur, in this case the price remains at its initial value $p(0)$, which means that a speculator is indifferent between buying and selling the asset. Second, uncertainty is resolved with the occurrence of the shock lowering the price to $p(T_\rho) = \frac{\delta}{r} - \lambda(S+\theta)$. In this case, it is strictly optimal to buy the asset as soon as he gets the opportunity to do so. In fact, consider a speculator who does not own the asset and contacts the market at time $t > T_\rho$. If he behaves according to the prescribed trading plan of purchasing the asset at time t and afterwards follow the optimal policy of keeping the asset, his value is $\frac{\delta}{r} - p(t)$. To check optimality, by the Bellman principle it suffices to rule out one-stage deviations, whereby a speculator deviates once from the prescribed plan and follows it thereafter. If the speculator deviates once by not purchasing the asset his value is

$$
V(0,t) = E\left[e^{-r(\tau-t)}\left(\frac{\delta}{r} - p(t)\right)\right]
$$

where τ is the next time the speculator will have the opportunity to contact the dealers. This is strictly less then $\frac{\delta}{r} - p(t)$ because of discounting. Hence, it is optimal to buy the asset back once uncertainty has been resolved, i.e. after T_ρ.

Next, let me consider what happens when the speculator has the opportunity to trade at $t < T_\rho$. In a market populated by a single speculator, I can easily compute the price path, which in turns determine the capital gains or losses the speculator compares the cash flows with. The expected price is given by

$$p^U(T_\alpha|T_\rho) = (1 - \varepsilon)p^R(T_\alpha|T_\rho) + \varepsilon p^S(T_\alpha|T_\rho)$$

where $p^S(T_\alpha|T_\rho) = \frac{\delta}{r} - \lambda(S + \theta)$ is the price in the case of the realization of the negative shock whereas $p^R(T_\alpha|T_\rho) = p(0)$ is the price if the no supply shock occurs. I can then use Lemma 2 to find the value of the severity of the shock θ that makes the investor indifferent between buying and selling the asset. Formally, the indifferent threshold θ^* is given by the following expression

$$
\begin{aligned}
\frac{\delta}{r + \alpha + \rho} &= [p^U(t) - \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(e^{-\rho(\tau_\alpha - t)}p^U(\tau_\alpha) + \int_t^{T_\alpha} \rho e^{-\rho(\tau_\rho - t)}p(\tau_\alpha|\tau_\rho)\,d\tau_\rho\right)d\tau_\alpha] \\
&= [p^U(t) - \left\{ \begin{array}{c} \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(e^{-\rho(\tau_\alpha - t)}p^U(t)\right. \\ \left. + \int_t^{T_\alpha} \rho e^{-\rho(\tau_\rho - t)}\left(\varepsilon\left(F - \lambda(S + \theta^*)\right) + (1 - \varepsilon)F\right)d\tau_\rho\right)d\tau_\alpha \end{array} \right\}] \\
&= [p^U(t) - \left\{ \begin{array}{c} \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(e^{-\rho(\tau_\alpha - t)}p^U(t)\right. \\ \left. + \int_t^{T_\alpha} \rho e^{-\rho(\tau_\rho - t)}\left(F - \varepsilon\lambda(S + \theta^*)\right)d\tau_\rho\right)d\tau_\alpha \end{array} \right\}] \\
&= p^U(t) - \frac{\alpha p^U(t)}{r + \alpha + \rho} + \frac{\alpha\left(F - \varepsilon\lambda(S + \theta^*)\right)}{r + \alpha + \rho} - \frac{\alpha\left(F - \varepsilon\lambda(S + \theta^*)\right)}{r + \alpha} \\
&= \frac{p^U(t)(r + \rho)}{r + \alpha + \rho} - \alpha\left(F - \varepsilon\lambda(S + \theta^*)\right)\frac{\rho}{(r + \alpha + \rho)(r + \alpha)},
\end{aligned}
$$

where I have substituted the prices in the different regions and simplified. Notice that as θ increases, the capital gain $q^c(t)$ increases, which makes more profitable to exploit the price swings rather than holding the asset until maturity. I can further solve to obtain a closed-form expression for the threshold:

$$\theta^* = \left[\frac{\delta(r + \alpha) + \alpha\left(\frac{\delta}{r} - \varepsilon\lambda S\right)\rho - p_0(r + \rho)(r + \alpha)}{\varepsilon\lambda\alpha\rho}\right].$$

Hence, the speculator is going to sell the asset at $t < T_\rho$ if and only if $\theta > \theta^*$. ∎

Proof of Corollary 4.

The threshold is increasing in the asset's dividends δ. The effects of the other parameters of interest can be found as follows. First, the effect of the market depth λ on the capital gain in expression (1.16) is clearly positive as :

$$\frac{\partial q}{\partial \lambda} = \alpha\varepsilon\,(S + \theta)\,\frac{\rho}{(r + \alpha + \rho)\,(r + \alpha)} > 0$$

Hence steeper demand curves of the long-term investors increase the speculator's incentive to sell when he expects negative shocks in the future.

The effect of the persistence of uncertainty is computed as

$$\frac{\partial \theta^*}{\partial \rho} = \frac{\left[\alpha\left(\frac{\delta}{r} - \varepsilon\lambda S\right) - \left(\frac{\delta}{r} - \lambda S\right)(r + \alpha)\right]\varepsilon\lambda\alpha\rho - \varepsilon\lambda\alpha\left[\delta\,(r + \alpha) + \alpha\left(\frac{\delta}{r} - \varepsilon\lambda S\right)\rho - \left(\frac{\delta}{r} - \lambda S\right)(r + \rho)(r + \alpha)\right]}{(\varepsilon\lambda\alpha\rho)^2}$$

$$= \frac{-\left(\frac{\delta}{r} - \lambda S\right)\rho - \delta + \left(\frac{\delta}{r} - \lambda S\right)(r + \rho)}{(\varepsilon\lambda\alpha\rho)^2} = \frac{-\lambda S r}{(\varepsilon\lambda\alpha\rho)^2} < 0$$

Hence, higher persistence of uncertainty (low ρ) reduce the speculator's incentive to liquidate his holdings at $t < T_\rho$.

Finally, the effect of the trading frictions α can be computed as follows

$$\frac{\partial \theta^*}{\partial \alpha} = \frac{\left(\delta + \left(\frac{\delta}{r} - \varepsilon\lambda S\right)\rho - \left(\frac{\delta}{r} - \lambda S\right)(r + \rho)\right)\varepsilon\lambda\alpha\rho - \varepsilon\lambda\rho\left[\delta\,(r + \alpha) + \alpha\left(\frac{\delta}{r} - \varepsilon\lambda S\right)\rho - \left(\frac{\delta}{r} - \lambda S\right)(r + \rho)(r + \right.}{(\varepsilon\lambda\alpha\rho)^2}$$

$$= \frac{-\varepsilon\lambda r\rho\delta + \left(\frac{\delta}{r} - \lambda S\right)(r + \rho)\varepsilon\lambda\rho r}{(\varepsilon\lambda\alpha\rho)^2} = sign\left(\frac{\delta}{r}\rho - \lambda S\,(r + \rho)\right)$$

Then, as long as δ is small enough, it is true that $\frac{\partial \theta^*}{\partial \alpha} < 0$. ∎

Proof of Lemma 6.

I employ the evolution of the fraction of speculators who own the asset, to derive the evolution of the price path in the two types of equilibrium. In the "cashing in on the crash" equilibrium, speculators start selling in the interval $[0, T_\rho)$. Then, we know from (1.2) that the price evolves according to:

$$\dot{p}\,(t) = \lambda\dot{x}\,(t) = -\alpha\lambda x\,(t)\,,$$

where we can employ the market clearing condition to rewrite the fraction of speculators $x(t)$ as

$$\lambda x(t) = p(t) - \frac{\delta}{r} + \lambda S,$$

which implies

$$\dot{p}(t) = -\alpha \left(p(t) - \frac{\delta}{r} + \lambda S \right).$$

I can solve the differential equation with initial condition $p(0) = p_0$ to obtain:

$$p(t) = \left(\frac{\delta}{r} - \lambda S \right) \left(1 - e^{-\alpha t} \right) + e^{-\alpha t} p_0.$$

However, I am interested in computing the price at time $t + s$, which can be obtained by first changing variables $\hat{p}(t) \equiv \left[p(t) - \left(\frac{\delta}{r} - \lambda S \right) \left(1 - e^{-\alpha t} \right) \right] \frac{1}{p_0} = e^{-\alpha t}$ and then by noting that the price in the next instant can be written as

$$\hat{p}(t + s) = e^{-\alpha t} e^{-\alpha s} = \left[p(t) - \left(\frac{\delta}{r} - \lambda S \right) \left(1 - e^{-\alpha t} \right) \right] \frac{1}{p_0} e^{-\alpha s}.$$

I can now revert the change of variables to get

$$p(t + s) = p(t) e^{-\alpha s} + \left(\frac{\delta}{r} - \lambda S \right) \left(1 - e^{-\alpha s} \right),$$

which is decreasing over time. Similarly, we can get the other expression in the text of the lemma by starting from $\dot{p}(t) = \lambda \alpha (1 - x(t))$, that is

$$\dot{p}(t) = \lambda \alpha - \lambda \alpha x(t) = \lambda \alpha - \alpha (p(t) - \frac{\delta}{r} + \lambda S),$$

which gives as a solution

$$p(t) = \left(\frac{\delta}{r} - \lambda S \right) \left(1 - e^{-\alpha s} \right) + \lambda \left(1 - e^{-\alpha s} \right) + e^{-\alpha t} p_0.$$

I can follow the same steps shown above for the other case to get the result stated in Lemma 6:

$$p(t + s) = p(t) e^{-\alpha s} + \lambda \left(1 - e^{-\alpha s} \right) + \left(\frac{\delta}{r} - \lambda S \right) \left(1 - e^{-\alpha s} \right),$$

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which is increasing over time. ∎

Proof of Proposition 7.

I start by conjecturing the price path in the two equilibria, and then I find the optimal trading strategies for the speculators and the conditions under which their trading strategies do indeed generate those price paths.

Consider a speculator who has the opportunity to trade at time $t < T_\rho$. To simplify notation, define $F = \frac{\delta}{r}$.

Part (i). I first find the conditions under which *cashing-in-on-the-crash* is an equilibrium. From Lemma 2, we know that it is optimal to sell the asset if and only if

$$u_a^c(a) = \frac{\delta}{r + \alpha + \rho} < q^c(t) = p^c(t) - \widetilde{p}(\tau_\alpha),$$

where

$$\widetilde{p}(\tau_\alpha) = \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)} (e^{-\rho(\tau_\alpha - t)} p^c(\tau_\alpha) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} p(\tau_\alpha|\tau_\rho) d\tau_\rho) d\tau_\alpha. \quad (1.17)$$

I know that $p^c(\tau_\alpha) < p^c(t)$ because in this region the price is strictly decreasing. I start simplifying the terms in expression (1.17); using Lemma 3 we can rewrite the first term as

$$\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)} (e^{-\rho(\tau_\alpha - t)} p^c(\tau_\alpha)) d\tau_\alpha \quad (1.18)$$

$$= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)} p^c(\tau_\alpha) d\tau_\alpha$$

$$= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)} \left(p^c(t) e^{-\alpha(\tau_\alpha - t)} + (F - \lambda S) \left(1 - e^{-\alpha(\tau_\alpha - t)} \right) \right) d\tau_\alpha$$

$$= \alpha \left(\frac{p^c(t)}{r + 2\alpha + \rho} + \frac{\alpha(F - \lambda S)}{(r + \alpha + \rho)(r + 2\alpha + \rho)} \right).$$

The second term in (1.17) takes into account that the speculator might come into contact with the market after T_ρ, which means that the price is a weighted average of the price after a shock

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(with weight ε) and of the price once the shock reveals to be temporary (with weight $(1 - \varepsilon)$):

$$p(\tau_\alpha | \tau_\rho) = \varepsilon \left(p(t) e^{-\alpha(\tau_\alpha - t)} + \left(1 - e^{-\alpha(\tau_\alpha - t)}\right)(F - \lambda(S + \theta) + \lambda)\right)$$

$$+ (1 - \varepsilon)\left(p(t) e^{-\alpha(\tau_\alpha - t)} + \left(1 - e^{-\alpha(\tau_\alpha - t)}\right)(F - \lambda S + \lambda)\right)$$

$$= p(t) e^{-\alpha(\tau_\alpha - t)} + \left(1 - e^{-\alpha(\tau_\alpha - t)}\right)(F - \lambda S + \lambda) - \varepsilon\lambda\theta\left(1 - e^{-\alpha(\tau_\alpha - t)}\right),$$

the previous expression also shows that the capital gain $q^c(t)$ is increasing in θ. I can use the previous expression to rewrite the second term in (1.17) as follows

$$\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(\int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} p(\tau_\alpha | \tau_\rho)\, d\tau_\rho\right) d\tau_\alpha \qquad (1.19)$$

$$= \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(\int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} \left[\begin{array}{c} p(t) e^{-\alpha(\tau_\alpha - t)} + \left(1 - e^{-\alpha(\tau_\alpha - t)}\right)(F - \lambda S + \lambda) \\ -\varepsilon\lambda\theta\left(1 - e^{-\alpha(\tau_\alpha - t)}\right) \end{array}\right] d\tau_\rho\right) d\tau_\alpha$$

$$= \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(p(t) e^{-\alpha(\tau_\alpha - t)}\left(1 - e^{-\rho(\tau_\alpha - t)}\right) + \left(1 - e^{-\rho(\tau_\alpha - t)}\right)\left(1 - e^{-\alpha(\tau_\alpha - t)}\right)(F - \lambda S + \lambda)\right.$$

$$\left. - \varepsilon\lambda\theta\left(1 - e^{-\rho(\tau_\alpha - t)}\right)\left(1 - e^{-\alpha(\tau_\alpha - t)}\right)\right) d\tau_\alpha$$

$$= (\alpha p^c(t)\left(\frac{\rho}{(r + 2\alpha)(r + 2\alpha + \rho)}\right) + \alpha(F - \lambda S + \lambda)\left(\frac{\alpha}{(r + \alpha)(r + 2\alpha)} - \frac{\alpha}{(r + 2\alpha + \rho)(r + \alpha + \rho)}\right)$$

$$- \alpha\varepsilon\lambda\theta\left(\frac{\alpha}{(r + \alpha)(r + 2\alpha)} - \frac{\alpha}{(r + 2\alpha + \rho)(r + \alpha + \rho)}\right)).$$

I can now define threshold $\underline{\theta}$ as the one that equates the cash flows with the capital gain:

$$\frac{\delta}{r + \alpha + \rho} = p^c(t) - \widetilde{p}(\tau_\alpha)$$

$$= p^c(t) - (\alpha p^c(t)\left(\frac{\rho}{(r + 2\alpha)(r + 2\alpha + \rho)}\right) + \alpha(F - \lambda S + \lambda)\mathbb{H} + \alpha\varepsilon\lambda\theta\mathbb{H}),$$

where, for notational simplicity, I have defined $\mathbb{H} = \left(\frac{\alpha}{(r+\alpha)(r+2\alpha)} - \frac{\alpha}{(r+2\alpha+\rho)(r+\alpha+\rho)}\right)$. Finally, the closed form expression for the threshold is

$$\underline{\theta}(p(t)) = \left[\frac{\delta}{r + \alpha + \rho} - p^c(t)\left(1 - \left(\frac{\alpha\rho}{(r + 2\alpha)(r + 2\alpha + \rho)}\right)\right) - \alpha(F - \lambda S + \lambda)\mathbb{H}\right]\frac{1}{\alpha\varepsilon\lambda\mathbb{H}}.$$

$$(1.20)$$

Following similar steps to the previous case, I can find the conditions under which buying

is optimal by supposing that for $t \in [0, T_\rho)$ the price is expected to rise and check that it is individually optimal to buy the asset rather than selling. Formally, I can substitute in expression (1.17) the different expected price path:

$$\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)} (e^{-\rho(\tau_\alpha - t)} p^c (\tau_\alpha)) d\tau_\alpha \tag{1.21a}$$

$$= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)} p^c (\tau_\alpha) d\tau_\alpha$$

$$= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)} \left(\lambda - (\lambda - p(t)) e^{-\alpha(\tau_\alpha - t)} + (F - \lambda S) \left(1 - e^{-\alpha(\tau_\alpha - t)} \right) \right) d\tau_\alpha$$

$$= \frac{\alpha \lambda}{r + \alpha + \rho} - \frac{\alpha \lambda}{r + 2\alpha + \rho} + \frac{\alpha p(t)}{r + 2\alpha + \rho} + \frac{\alpha (F - \lambda S)}{r + \alpha + \rho} - \frac{\alpha (F - \lambda S)}{r + 2\alpha + \rho}$$

$$= \alpha \lambda \left(\frac{\alpha}{(r + \alpha + \rho)(r + 2\alpha + \rho)} \right) + \frac{\alpha p(t)}{r + 2\alpha + \rho} + \alpha (F - \lambda S) \left(\frac{\alpha}{(r + \alpha + \rho)(r + 2\alpha + \rho)} \right).$$

By substituting (1.21a) in the optimality condition identified in Lemma 2, I can find a different threshold for the severity of the shock:

$$\bar\theta (p(t)) = \left[\frac{\frac{\delta}{r+\alpha+\rho} + \alpha \lambda \left(\frac{\alpha}{(r+\alpha+\rho)(r+2\alpha+\rho)} \right) - p^c (t) \left(1 - \left(\frac{\alpha \rho}{(r+2\alpha)(r+2\alpha+\rho)} \right) \right)}{-\alpha (F - \lambda S + \lambda) \mathbb{H}} \right] \frac{1}{\alpha \varepsilon \lambda \mathbb{H}}$$

This completes part (i).

Part (ii). Notice that it is optimal to buy the asset if and only if the following conditions holds

$$\frac{\delta}{r + \alpha + \rho} > p^c (t) - \widetilde{p} (\tau_\alpha) \tag{1.22}$$

Comparing condition (1.18) with (1.21a) shows that the threshold $\bar\theta (p(t))$ that solves (1.22) is higher than $\underline\theta (p(t))$.

It is now important to notice a key difference of these threshold with the one, $\hat\theta$, identified in Proposition 3: when speculators interact with each other in the market, the thresholds depend (negatively) on the price at time t, i.e. $\frac{\partial \bar\theta(p_t)}{\partial p_t} < 0$ and $\frac{\partial \theta(p_t)}{\partial p_t} < 0$. ∎

Proof of Proposition 8.

Part $(Crash)$ The result on the crash phase of the equilibrium directly follows from the previous proposition in a cashing-in-on-the-crash equilibrium. Suppose there exists a lower bound for the price $p^* \geq 0$, such that the price never go below this threshold (next point shows

this exists and is unique). Then, a speculator who has the opportunity to trade at $t < T_\rho$ will start selling his holdings when he expects others to do the same in the future and when the price $p(t)$ he obtains by doing so is greater than the lower bound for the price p^*. Both the initial price $p(0)$ and the initial holdings $x(0)$ for the speculators need to be high enough to ensure the existence of this equilibrium.[37] In particular, if $p(0) < p^*$, the only equilibrium that emerges is the leaning-against-the-wind one. If $x(0)$ is close to zero, the speculator who has an opportunity to trade at time t expects the price to move very little before the arrival of the shock at T_ρ, which makes it optimal for him to continue to hold the asset.

Part (*Market Freeze*) Now I show that, in a cashing-in-on-the-crash equilibrium, the price cannot decline indefinitely. The existence of a unique price p^* at which trading activities come to an halt follows from the fact that the speculators' capital gains are decreasing in the price and are compared to the cash flow of the asset which is instead constant and independent of $p(t)$. For $p(t) = 0$ the speculators have no incentive to sell the asset. This means that, at that price, u_a is strictly greater than $q(t)$. By a continuity argument, this is true also for $p(t)$ positive but arbitrarily small. However if, as assumed, $p(0)$ is sufficiently high the potential capital gains are above u_a and are continuously decreasing in $p(t)$. This means that will exist a price at which the speculator is indifferent between selling and keeping the asset as defined by the price that equates the value and the cost of holding the asset, i.e. $u_a = q(t)$, as $q(t)$ is a function of t only through the price $p(t)$. This threshold is unique because the probability that in the next instant there will be a shock is constant, as T_ρ is distributed according to a Poisson process. Hence, a speculator that can sell at a price just ε above the threshold p^* will do it as he will be compensated by the arrival of the shock θ, whereas once the price reaches the level p^* speculators have no incentive to trade the asset.

Part (*Recovery*). As for the proof of Proposition 3, I start with a speculator who meets a dealer at $t > T_\rho$. After T_ρ, if $p(T_\rho) = F$ a speculator is indifferent between buying and selling the asset, then given my tie-breaking rule, they do not buy, and the price stays constant at the fundamental value. If at time T_ρ a shock of severity θ is realized, then it is strictly optimal for the investor to buy the asset as soon as he gets the opportunity to do so (in both equilibria: when the price was increasing at $t < T_\rho$, but since it cannot go above F, it will still be below

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[37]Notice that the condition on $x(0)$ can be relaxed if I allow the speculators to short-sell the asset.

F, or it was decreasing and then after the shock the price is even lower). Consider, in fact, a speculator who does not own the asset and contacts the market at time $t > T_\rho$. If he behaves according to the prescribed trading plan of purchasing the asset at time t and afterwards follow the optimal policy of keeping the asset, his value is $F - p(t)$, which is positive as discussed above. To check optimality, by the Bellman principle it suffices to rule out one-stage deviations, whereby a speculator deviates once from the prescribed plan and follows it thereafter. If the speculator deviates once by not purchasing the asset his value is

$$V(0, t) = E\left[e^{-r(\tau - t)}(F - p(t))\right]$$

where τ is the next instant at which the speculator has the opportunity to contact the market. This is strictly less then $F - p(t)$ because the price is strictly increasing over $[T_\rho, \infty)$ and because of discounting. Hence, he is not going to deviate from the prescribed strategy.

Consider an investor who owns the asset. The value of following the prescribed plan of holding the asset is F. If the agent deviates once and sell at time $\tau > t$ his value is

$$\begin{aligned}
&\mathbb{E}_t\left[\int_t^\tau e^{-r(u-t)}\delta du + e^{-r(\tau - t)}(p(z) + V(0, z))\right] \\
= \quad &F + \mathbb{E}_t\left[e^{-r(\tau - t)}((p(z) + V(0, z) - F))\right]
\end{aligned}$$

this is lower than F because $(p(z) + V(0, z) - F) < 0$ as shown above that $V(0, t) < F - p(t)$. Hence, speculators who own the asset are strictly better off by holding their assets for every $t > T_\rho$. This completes the proof of the proposition. ■

Proof of Proposition 9.

This follows from Lemma 6 and the cashing-in-on-the-crash equilibrium of Proposition 7. As the price changes as rate α, and in a cashing-in-on-the-crash equilibrium it first decrease for $t < T_\rho$ and then reverts toward the fundamental value of the asset, higher α (lower trading frictions) leads to a faster-changing price. ■

Proof of Proposition 10.

To compute the effects of different parameters on speculators' incentives I separately analyze the effect on the cash flow and on the capital gains terms. This allows me to formally show the results depicted in Figures 1-5 and 1-6. The left hand side of the optimality condition in

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Lemma 2, $\frac{\delta}{r+\alpha+\rho}$ is decreasing in both α and ρ as depicted by the blue curves in the Figures 1-5 and 1-6.

The capital gain in 1.19, instead, is composed of three terms, and I am going to analyze each one of them. First we have the effect of parameters on the coefficient of the price is positive:

$$\frac{\partial\left(\frac{\alpha\rho}{(r+2\alpha)(r+2\alpha+\rho)}\right)}{\partial\rho} = \frac{\alpha\left(r+2\alpha\right)\left(r+2\alpha+\rho\right) - \alpha\rho\left(r+2\alpha\right)}{\left(r+2\alpha\right)^2\left(r+2\alpha+\rho\right)^2} = \frac{1}{\left(r+2\alpha+\rho\right)^2} > 0.$$

The effect of α can be similarly computed as follows:

$$\frac{\partial\left(\frac{\alpha\rho}{(r+2\alpha)(r+2\alpha+\rho)}\right)}{\partial\alpha} = \frac{\rho\left(r+2\alpha\right)\left(r+2\alpha+\rho\right) - 2\alpha\rho\left[\left(r+2\alpha\right)+\left(r+2\alpha+\rho\right)\right]}{\left(r+2\alpha\right)^2\left(r+2\alpha+\rho\right)^2} = \frac{r^2+r\rho-4\alpha^2}{\left(r+2\alpha\right)^2\left(r+2\alpha+\rho\right)^2} \lessgtr 0,$$

this shows that the effect depends on the value of α and ρ: specifically, it is positive for high value of ρ. Then we have the coefficient $\mathbb{H}$ for the second and third term which is increasing in ρ:

$$\frac{\partial\mathbb{H}}{\partial\rho} = \frac{\partial\left(\frac{\alpha}{(r+\alpha)(r+2\alpha)} - \frac{\alpha}{(r+2\alpha+\rho)(r+\alpha+\rho)}\right)}{\partial\rho} > 0.$$

The effect of α can be found by decomposing $\mathbb{H}$ as

$$\frac{\partial\left(\frac{\alpha^2}{(r+2\alpha)(r+\alpha)}\right)}{\partial\alpha} = \frac{2r^2\alpha+3\alpha^2 r}{\left(r+2\alpha\right)^2\left(r+\alpha\right)^2} > 0$$

$$\frac{\partial\left(\frac{\alpha^2}{(r+2\alpha+\rho)(r+\alpha+\rho)}\right)}{\partial\alpha} = \frac{2r^2\alpha+3\alpha^2 r+3\alpha^2\rho+4\alpha r\rho+2\alpha\rho^2}{\left(r+2\alpha+\rho\right)^2\left(r+\alpha+\rho\right)^2} > 0.$$

This means that for high value of ρ, the capital gains $q\left(t\right)$ first decrease as a function of α, but then increases as depicted in panel (b) of figure 1-6.

Finally, I can investigate the effect of market depth λ. The effect on 1.19 is positive if $\left(1-S\right)-\varepsilon\theta > 0$, which is true for small enough probability of the shock ε. ∎

Proof of Proposition 11.

Since the cost lowers the capital gain, it decreases the speculators' incentive to profit from price swings. In other words, the threshold for the shock θ that makes the traders indifferent between holding the asset and profit from price swings need to increase. In fact, suppose a

speculator meeting coming into contact with the market at time $t < T_\rho$, sells the asset if and only if the following condition holds

$$\frac{\delta}{r + \alpha + \rho} > (p(t) - c) - \widetilde{p}(\tau_\alpha)$$

which is the same as in Lemma 2, except for the introduction of the transaction cost, which lowers the price gained by the speculator in the case in which he sells the asset. This means that a transaction cost reduces the speculators' incentives to cash in on the crash.

To show that the introduction of a transaction cost reduces speculators' incentive to profit from fluctuations, we can follow the same procedure as in Proposition 7, but including the tax c in the capital gain $q(t)$. We can rewrite the problem of an investor who gains access to the market at time t which has to pay a transaction cost c as

$$\max_{a' \geq 0} \int_t^{T_{\alpha\rho}} e^{-r(s-t)} \delta a' ds - \left\{ (p(t) + c) - \mathbb{E}\left[e^{-r(T_\alpha - t)} \left\{ (\mathbb{I}_{\{T_\alpha < T_\rho\}} p^U(T_\alpha) + \mathbb{I}_{\{T_\alpha > T_\rho\}} p^U(T_\alpha | T_\rho)) - c \right\} \right] \right\} a' \tag{1.23}$$

The only difference with Lemma 2 is that the investor who buys (sells) the asset will pay (receive) the price $p(t) + c$ ($p(t) - c$). As in Lemma 2 we can compute the expected utility flows that the speculator obtains by holding portfolio a.

$$\begin{aligned}
u^U(a) &= \mathbb{E}\left[\int_0^{T_{\alpha\rho} - t} e^{-rs} \delta a ds \right] = \mathbb{E} \int_0^\infty \left[\int_0^{T_{\alpha\rho}} e^{-rs} \delta a ds \right] (\alpha + \rho) e^{-(\alpha+\rho)T_{\alpha\rho}} dT_{\alpha\rho} \\
&= a^U \left(\frac{\delta}{r + \alpha + \rho} \right)
\end{aligned}$$

To derive the expected value of the price, we use the fact that $T_\alpha - t$ and $T_\rho - t$ are two independent exponentially distributed random variables:

$$\begin{aligned}
&\mathbb{E}\left[e^{-r(T_\alpha - t)} \left\{ \mathbb{I}_{\{T_\alpha < T_\rho\}} \left(p^U(\tau_\alpha) - c \right) + \mathbb{I}_{\{T_\alpha > T_\rho\}} \left(p^U(T_\alpha | T_\rho) - c \right) \right\} \right] \\
&= \int_t^\infty e^{-r(\tau_\alpha - t)} \left[e^{-\rho(\tau_\alpha - t)} \left(p^U(\tau_\alpha) - c \right) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} \left(p^U(\tau_\alpha | \tau_\rho) - c \right) \right] \alpha e^{-\alpha(\tau_\alpha - t)} d\tau_\rho d\tau_\alpha \\
&= \int_t^\infty e^{-r(\tau_\alpha - t)} \left[e^{-\rho(\tau_\alpha - t)} p^U(\tau_\alpha) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} p^U(\tau_\alpha | \tau_\rho) \right] \alpha e^{-\alpha(\tau_\alpha - t)} d\tau_\rho d\tau_\alpha - \frac{\alpha c}{r + \alpha}
\end{aligned}$$

where the second equality follows from Lemma 2.

The speculators who now need to pay the Tobin tax c and do not own the asset will buy it if and only if:

$$\frac{\delta}{r + \alpha + \rho} - \frac{rc}{\alpha + r} > p(t) - \widetilde{p}(\tau_\alpha).$$

Hence, the speculators have less incentives to buy the asset. This shows that there exists a high enough transaction cost $\bar{c}$, above which the speculators finds it optimal to abstain from trading outright. ∎

Proof of Proposition 12.

The result that the introduction of a Tobin tax might actually increase speculators' incentives to sell the asset at time $t < T_\rho$, follows from Proposition 10 and the assumption that the liquidity provided by long-term investors, $\lambda(c)$, is an increasing function of the transaction cost. In fact, Proposition 10 shows that speculators have higher incentives to sell their holdings in less-liquid markets, namely when λ is high. Suppose now that for a given λ, the condition identified in Lemma 2 would predict them to purchase the asset. Consider now the introduction of the tax, which increases λ to $\lambda' > \lambda$; if the market depth function $\lambda(\cdot)$ is sufficiently sensitive to c, such increase might increase the potential capital gains so much that now it is optimal for the speculators to actually sell the asset. Hence, it follows the statement of the proposition that when the introduction of transaction costs reduce the liquidity of the market, this might have destabilizing effects. ∎

Proof of Proposition 13.

The proof follows the argument first proposed by Frankel and Pauzner (2000). The idea of the proof is that the existence of dominance regions shown in Proposition 7 starts an iterative contagion effect that spreads throughout the parameter space. Frankel and Burdzy (2005) show that a similar argument can be used when θ_t follows an arbitrary mean-reverting process, as long as the drift μ is a linear function of the state θ_t.

Let start with a speculator who has the opportunity to trade when θ is at right of $\bar{\theta}(p(t))$: it is dominant for him to sell. Now consider a speculator slightly to the left of $\bar{\theta}(p(t))$, he will sell his asset holdings too. In fact, if he was observing a shock of size $\bar{\theta}(p(t))$, he was at most indifferent between buying or selling the asset, but now he knows that if θ changes stochastically over time, small perturbations to the severity of the shock θ might approach the dominance boundary, at such time other speculators will find it optimal to sell, which makes

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the speculator not indifferent anymore. Then, we can now define a new boundary $\bar{\theta}^1$. When speculators believe that the shock hitting the market in the future is exactly $\bar{\theta}^1$, they should be indifferent between buying or selling the asset on the worst-case belief that other speculators choose to sell to the right of $\bar{\theta}$. By repeating this reasoning we obtain the limit boundary $\bar{\theta}^\infty$, which is the limit of the sequence, and is an equilibrium because on each boundary $\bar{\theta}^n$ the speculator was indifferent between buying and selling the asset.

We can now start a similar iteration from the left boundary $\underline{\theta}\left(p\left(t\right)\right)$, but using translations of the boundary $\bar{\theta}^\infty$, the reason for this way of proceeding will be clear soon. We start with a translation where buying is dominant $\left(\theta < \underline{\theta}\left(p\left(t\right)\right)\right)$. We then iterate constructing the other curves as the right-most translation of $\underline{\theta}'_0$. The limit of these translation being $\underline{\theta}_\infty$. Since we started with translations of $\bar{\theta}^\infty$, it is not necessarily an equilibrium. However, if the speculator who contacts the dealer when the perceived shock is on $\underline{\theta}_\infty$, he expects all the other speculators to play according to that, then there must be a point A where he is indifferent, otherwise would strictly prefer buying. Let B the point on $\bar{\theta}^\infty$ at the same height as A.

We need to establish that A and B coincide in order to show that there exists a unique threshold. Let us compare two speculators, one in A and one in B. They expect the state to have the same relative dynamics because $\bar{\theta}^\infty$ and $\underline{\theta}_\infty$ have the same shape. Now consider a given path of changes in θ. Given this path, speculators in A and B expect the same path of θ_t. Suppose by contradiction that A and B were different, then the θ that the speculator in B expects would at all times exceed the θ that A expects by an amount equal to the initial difference in the θ's. Since the relative payoff to sell is increasing in θ, B's payoff from choosing selling would be higher than A's. But this cannot be, since both A and B are indifferent between the two strategy. Therefore, the curves $\bar{\theta}^\infty$ and $\underline{\theta}_\infty$ coincide and the equilibrium is unique. ∎

1.10 Appendix B- Evidence of Strategic Motive

Figure 1-8: European Political Uncertainty Index
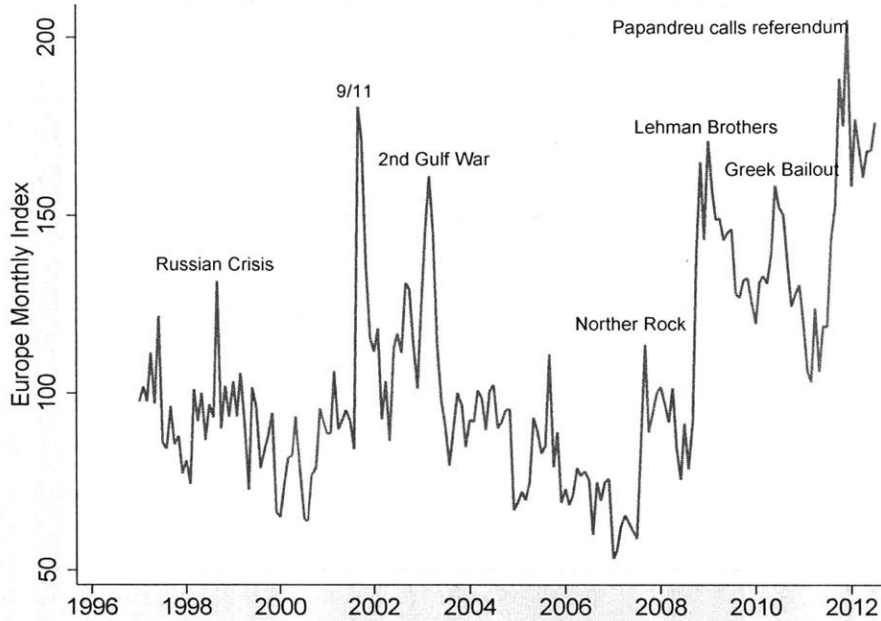
Notes: The panel above plots the European Political Uncertainty index proposed by Baker et al. (2011) for the period 1997-2012. The index is constructed using two types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. A second component uses disagreement among economic forecasters as a proxy for uncertainty.

Figure 1-9: MMMFs exposure to the PIIGS
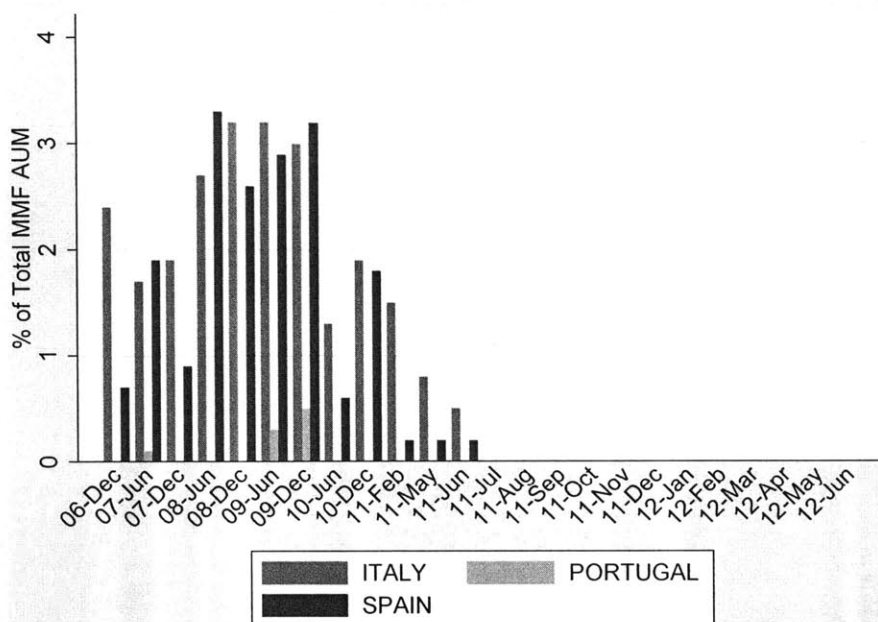
Notes: The panel above plots MMFs exposure, measured as the fraction of assets under management, to Portugal, Italy and Spain for the period December 2006 to June 2012. MMFs had no exposure to Greece and Ireland starting in 2010 (*Source*: Fitch and ICI).

Figure 1-10: Average Asset Maturity
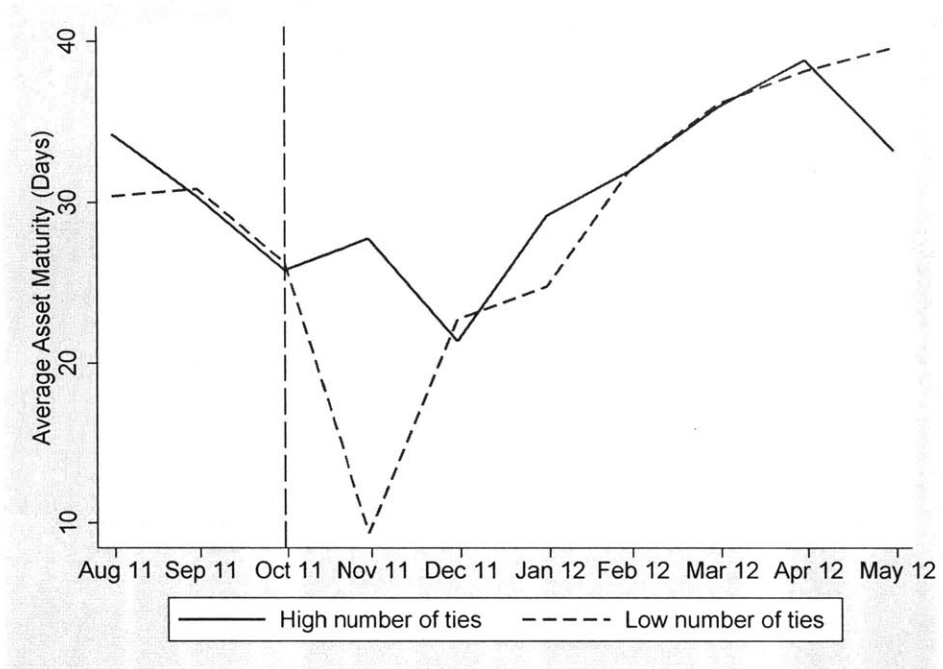
Notes: The panel above plots the average asset maturity issued by European institutions that have above (the blue continuous line) and below (the red dashed line) average number of borrowing relationships with MMFs for the period August 2011-May 2012. The vertical line identifies the post period after October, 2011.

Figure 1-11: Average Asset Yield
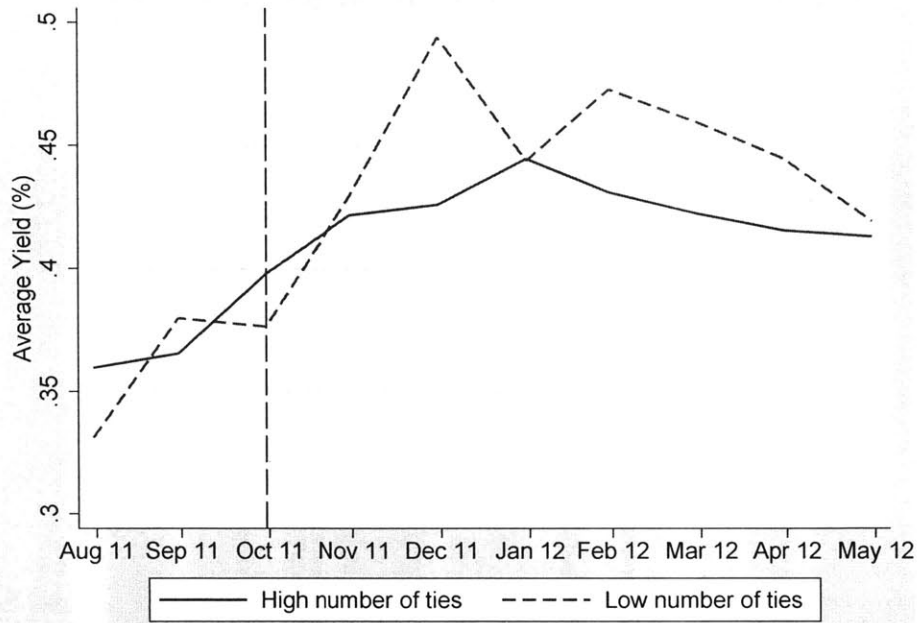
Notes: The panel above plots the average yield on the assets issued by European institutions that have above (the blue continuous line) and below (the red dashed line) average number of borrowing relationships with MMFs for the period August 2011-May 2012. The vertical line identifies the post period after October, 2011.

Figure 1-12: Event Study: Flight from Maturity
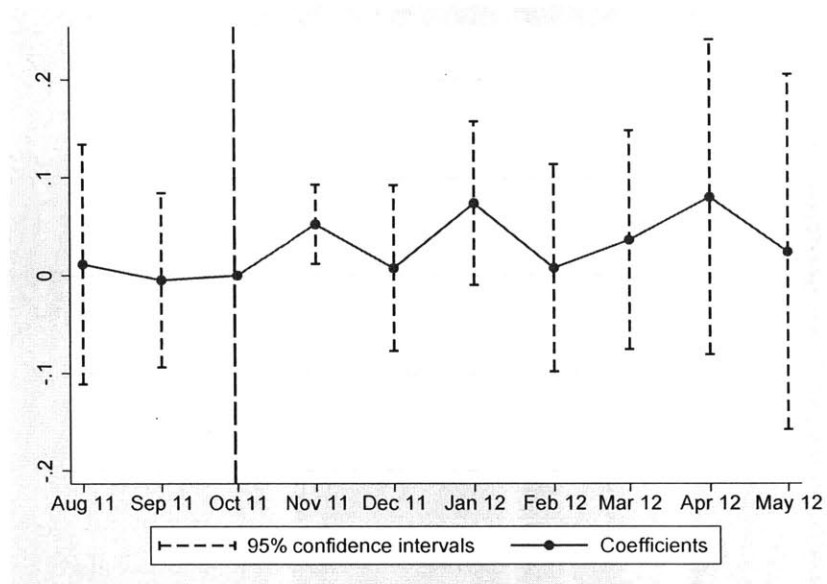
Notes: The panel above plots the interaction coefficients from the OLS regression below. The dependent variable is the average maturity of the assets issued by European institutions. The main independent variable is the interaction of the issuer number of borrowing relationships and monthly indicator variables. The vertical line identifies the post period after October 2011. I include time-fixed effects and issuer-fixed effects.

$$Issuer\ Maturity_{g,t} = \sum_{\tau \neq t_0} \beta_\tau Issuer\ Ties_{g,\ Aug\ 11} \mathbf{1}_{(\tau = t)} + \gamma_t + \phi_g + \varepsilon_{g,t}$$

Figure 1-13: Event Study: Cost of Capital
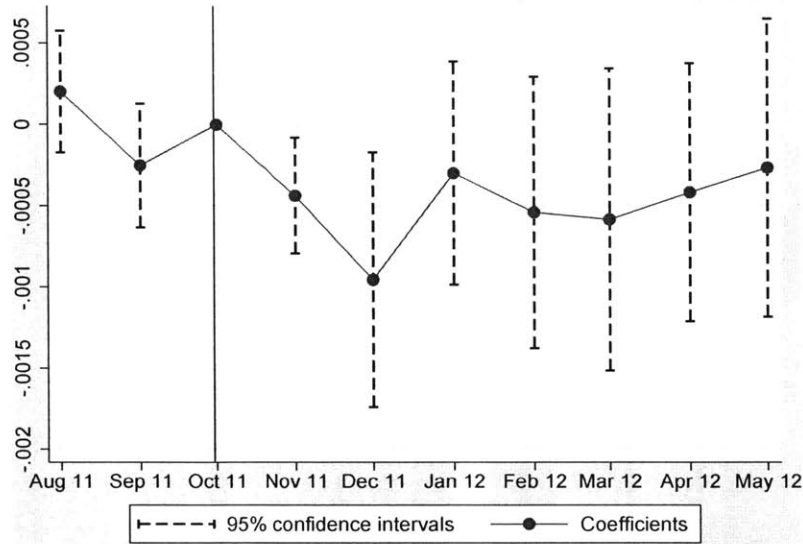
Notes: The panel above plots the interaction coefficients from the OLS regression below. The dependent variable is the average yield on the assets issued by European institutions. The main independent variable is the interaction of the issuer number of borrowing relationships and monthly indicator variables. The vertical line identifies the post period after October 2011. I include time-fixed effects and issuer-fixed effects.

$$Issuer\ Yield_{g,t} = \sum_{\tau \neq t_0} \beta_\tau Issuer\ Ties_{g,\ Aug\ 11} \mathbf{1}_{(\tau=t)} + \gamma_t + \phi_g + \varepsilon_{g,t}$$

Figure 1-14: Kernel Distribution of MMMFs' Portfolio Liquidity

Fraction of assets maturing in the next seven days as of August, 2011
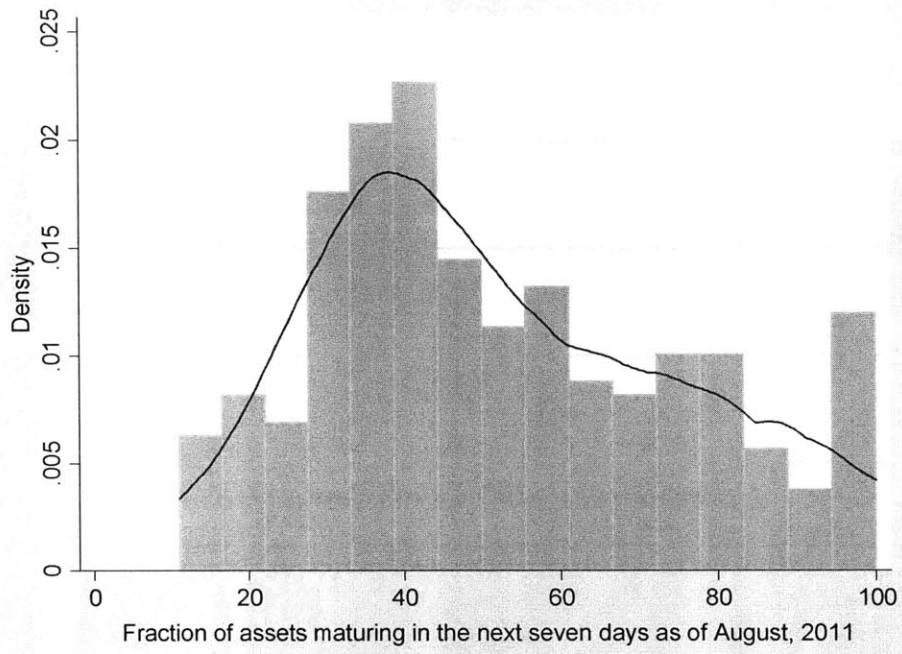
Notes: The panel above plots the kernel density of the fraction of assets maturing in the next seven days for all taxable funds in the period August 2011-May 2012.

Figure 1-15: MMMFs Exposure to the Eurozone
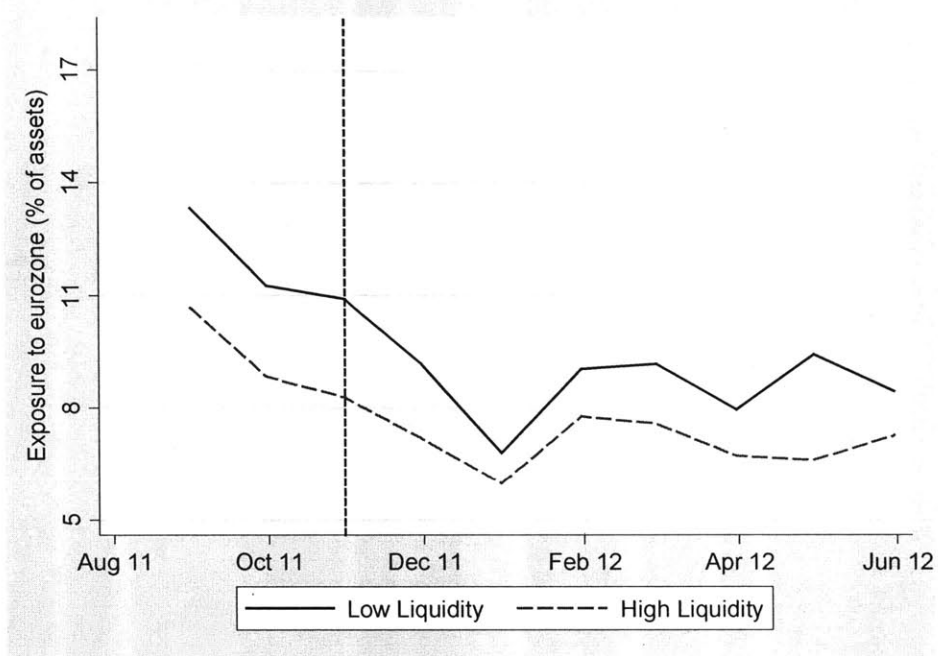
Notes: The panel above plots the MMFs exposure to the euro area measured as the fraction of assets under management for the period August 2011-May 2012 for funds with above (the red dashed line) and below (the blue connected line) average share of assets maturing in the next seven days.

Figure 1-16: Event Study: Uncertainty Shock and Exposure to Eurozone
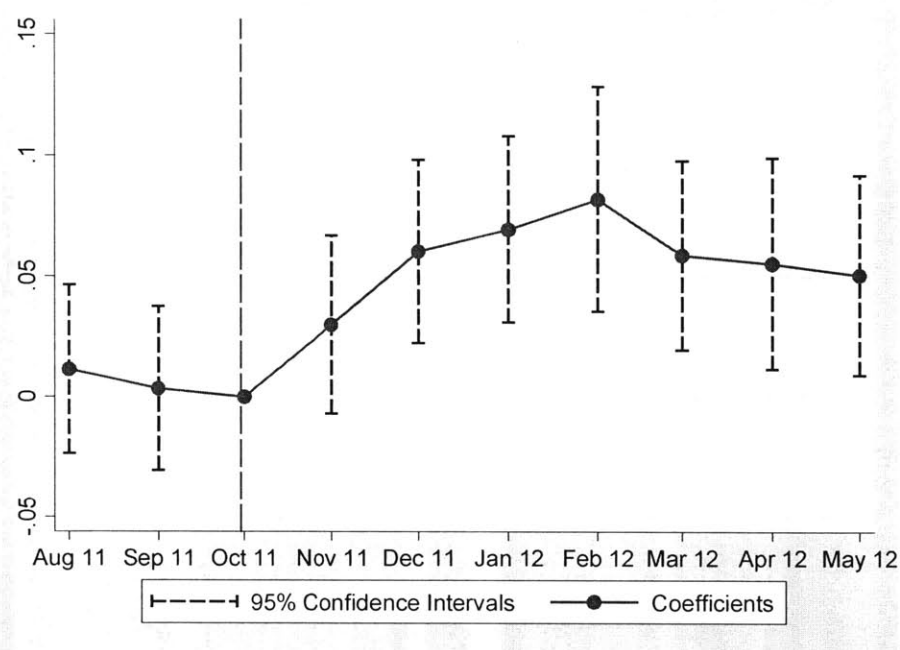
Notes: The panel above plots the interaction coefficients from the OLS regression below. The dependent variable is the fund exposure to the euro area. The main independent variable is the interaction of the fund liquidity and monthly indicator variables. The vertical line identifies the post period after October 2011. We include time-fixed effects and fund-fixed effects.

$$Euro\ Exposure_{i,t} = \sum_{\tau \neq t_0} \beta_\tau Liquidity_{i,Aug\ 11} \mathbf{1}_{(\tau=t)} + \gamma_t + \eta_i + \varepsilon_{i,t}$$

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Table 1.1: Summary Statistics

	Mean	Median	SD	Min	Max
Panel A: Fund Characteristics					
Assets (millions)	6832.16	1548.50	14110.18	7.90	122891.80
Monthly gross yield (%)	0.03	0.01	0.05	0	0.33
Weighted average maturity	38.84	41.00	12.78	1.00	60.00
Fraction of assets maturing in next 7 days (%)	54.69	49.00	24.74	4.00	100.00
Charged expense ratio	0.16	0.14	0.09	0	0.45
Spread	-0.02	-0.01	0.06	-0.09	0.25
Panel B: Holdings information					
Domestic banks obligations (%)	0.70	0.00	2.90	0	48.00
Foreign banks obligations (%)	7.86	0.00	11.90	0	57.00
Time deposits (%)	1.70	0.00	5.17	0	51.00
Floating rate notes (%)	12.83	7.00	16.69	0	88.00
Asset-backed commercial paper (%)	5.49	0.00	9.31	0	61.00
Repurchase agreements (%)	25.62	18.00	25.49	0	100.00
U.S. treasuries (%)	18.07	5.00	29.11	0	100.00
Panel C: Region of risk					
Eurozone exposure (% of assets)	8.49	5.02	9.88	0	95.92
Europe non-eurozone exposure (% of assets)	10.77	8.95	10.94	0	57.94
Americas exposure (% of assets)	58.21	54.81	27.21	0	100.00
Asia exposure (% of assets)	3.89	0	5.57	0	44.59
Panel D: Securities and Issuers Characteristics					
Average Yield (%)	0.36	0.35	0.21	0.05	1.17
Average Maturity (days)	27	25	20	1	74
Number of Funding Relationships	54	40	48	1	123
CDS premium (basis points)	151	113	81	33	290

Notes: This table reports summary statistics for the taxable money market funds in my data. The sample period is August 2011-May 2012. Panel A reports fund-month level summary statistics. Fund-level gross yield is the value reported on form N-MFP. Spread is the fund seven-day yield net of the three month Treasury bill. Panel B reports the fraction of total assets invested in the different security types. Panel C reports the exposure to different regions of risk as the fraction of the fund asset invested in that region. Panel D reports the average maturity and yields of the assets issued by the European institutions. The credit default spread are extracted from Datastream. the number of ties is the number of borrowing relationships that the European issuers have in August 2011.

Table 1.2: Summary Statistics by MMFs Portfolio Liquidity

	All Prime Funds Average	Low-Liquidity Funds Average	High-Liquidity Funds Average
Assets (millions of dollars)	6953	7,732	6,363
Weighted average maturity (days)	38	41	34
Fraction of ABCP	6.02%	9.50%	3.15%
Fraction of repos	25.55%	13.90%	36.26%
Fraction of U.S. Treasury securities	13.73%	8.15%	11.22%
Fraction of other U.S. government agency securities	14.10%	14.42%	16.54%
Fraction of foreign bank obligations	8.52%	12.60%	5.43%
Fraction of domestic bank obligations	0.76%	1.20%	0.39%
Fraction of Time deposits	1.80%	1.45%	2.30%
7-Day Gross Yield	0.035	0.044	0.031

Notes: This table reports summary statistics for taxable money market funds in my data. The sample period is August 2011-May 2012 divided by funds' portfolio liquidity. Low-liquidity funds have below average fraction of assets maturing in the next seven days, while high-liquidity funds have an above average fraction of their assets maturing in the next seven days. All differences are statistically significant at 1% level. All the information are reported on form N-MFP every month to the SEC.

Table 1.3: Uncertainty and Strategic Motive

	(1) Δ % AUM Invested	(2) Δ Amount Invested	(3) Δ % AUM Invested	(4) Δ Amount Invested
Number of Ties$_{lug\,2011}$ × Post indicator $_{Oct\,2011}$	0.00252*** (0.000706)	118,425** (58,415)		
Number of Ties$_{lug\,2011}$ × Post indicator $_{Feb\,2012}$			-0.00176*** (0.000604)	-100,312* (59,975)
Time fixed effects	✔	✔	✔	✔
Issuer fixed effects	✔	✔	✔	✔
Observations	13,719	13,719	10,237	10,237
R-squared	0.001	0.001	0.009	0.004

Notes: The dependent variable in columns (1) and (3) is the change in the fraction of assets invested in the issuer's securities by each fund, whereas in columns (2) and (4) it is the change in the dollar amount invested in the issuer's asset by each fund. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012 for the model estimated in columns (1) and (2) and from October 2011 to May 2012 in columns (3) and (4).

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.4: The Effect of Issuer Riskiness

	(1) Δ % AUM Invested	(2) Δ Amount Invested	(3) Δ % AUM Invested	(4) Δ Amount Invested
Number of Ties$_{Aug\ 2011}$ × Post indicator$_{Oct\ 2011}$	0.00679*** (0.00143)	289,519*** (98,146)		
Number of Ties$_{Aug\ 2011}$ × Post indicator$_{Feb\ 2012}$			-0.00489*** (0.00122)	-109,737 (118,248)
Issuer CDS	-0.000459 (0.00122)	-71.97 (88,128)	0.0232 (0.0161)	144,948 (231,731)
Issuer CDS× Post indicator$_{Oct\ 2011}$	-0.00260*** (0.000605)	-184,804*** (43,200)		
Issuer CDS× Post indicator$_{Feb\ 2012}$			0.00241** (0.000865)	11,634 (172,602)
Time fixed effects	✔	✔	✔	✔
Issuer fixed effects	✔	✔	✔	✔
Observations	4,805	4,805	4,083	4,083
R-squared	0.011	0.009	0.011	0.005

Notes: The dependent variable in columns (1) and (3) is the change in the fraction of assets invested in the issuer's securities by each fund, whereas in columns (2) and (4) it is the change in the dollar amount invested in the issuer's asset by each fund. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Issuer CDS is the time series of CDS prices extracted from Datastream. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012 for the model estimated in columns (1) and (2) and from October 2011 to May 2012 in columns (3) and (4).

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.5: Flight from Maturity

	(1)	(2)	(3)	(4)	(5)	(6)
Post indicator $_{Aug\ 2011}$	-7.712***					
	(0.581)					
Post indicator $_{Feb\ 2012}$				21.13***		
				(6.113)		
Number of Ties $_{Aug\ 2011}$	-0.0491***	-0.0479***		0.166*	0.107***	
	(0.00511)	(0.00509)		(0.0893)	(0.0379)	
Number of Ties $_{Aug\ 2011}$ × Post indicator $_{Oct\ 2011}$	0.0117*	0.0126*	0.0534***			
	(0.00668)	(0.00666)	(0.00334)			
Number of Ties $_{Aug\ 2011}$ × Post indicator $_{Feb\ 2012}$				-0.166*	-0.118***	-0.0570***
				(0.0909)	(0.0381)	(0.0156)
Time fixed effects		✔	✔		✔	✔
Issuer fixed effects			✔			✔
Observations	10,891	10,891	10,891	12,563	12,563	12,563
R-squared	0.062	0.071	0.794	0.118	0.162	0.807

Notes: The dependent variable is the average maturity of the assets issued by each single institutions. It includes both commercial paper and repurchase agreements. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Issuer CDS is the time series of CDS prices extracted from Datastream. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012 for the model estimated in columns (1)-(3) and from October 2011 to May 2012 in columns (4)-(6).

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

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Table 1.6: European Institutions' Cost of Capital

	(1)	(2)	(3)	(4)
Post indicator $_{Aug\ 2011}$	0.140***			
	(0.00586)			
Number of Ties $_{Aug\ 2011}$	0.000516***		-0.000248***	
	(4.22e-05)		(4.04e-05)	
Number of Ties $_{Aug\ 2011}$ × Post indicator $_{Oct\ 2011}$	-0.000495***	-0.000299***		
	(5.56e-05)	(3.07e-05)		
Post indicator $_{Feb\ 2012}$			-0.0505***	
			(0.00619)	
Number of Ties $_{Aug\ 2011}$ × Post indicator $_{Feb\ 2012}$			0.000104*	0.000156***
			(5.86e-05)	(3.11e-05)
Time fixed effects	.	✔	.	✔
Issuer fixed effects	.	✔	.	✔
Observations	9,815	9,815	9,552	9,552
R-squared	0.139	0.770	0.029	0.741

Notes: The dependent variable is the average maturity of the assets issued by each single institutions. It includes both commercial paper and repurchase agreements. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Issuer CDS is the time series of CDS prices extracted from Datastream. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012 for the model estimated in columns (1)-(3) and from October 2011 to May 2012 in columns (4)-(6).

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.7: The Effect of Fund Distress

	(1) Δ % AUM Invested	(2) Δ % AUM Invested	(3) Δ % AUM Invested
Number of Ties$_{Aug\ 2011}$ × Post indicator $_{Oct\ 2011}$	0.00682*** (0.00138)	0.00626*** (0.00166)	0.00621*** (0.00122)
Issuer CDS	-0.000457 (0.00126)	0.000680 (0.000730)	-0.000569 (0.00125)
Issuer CDS× Post indicator $_{Oct\ 2011}$	-0.00259*** (0.000657)	-0.00303*** (0.000862)	-0.00233*** (0.000608)
Breaking the Buck	-14.97 (144.0)		-19.82 (161.0)
Breaking the Buck× Post indicator $_{Oct\ 2011}$	28.51 (225.6)		36.30 (250.6)
Time fixed effects	✔	✔	✔
Issuer fixed effects	✔	✔	✔
Observations	4,768	4,093	4,553
R-squared	0.011	0.013	0.011

Notes: The dependent variable is the change in the fraction of assets invested in the issuer's securities by each fund, whereas in columns (2) and (4) it is the change in the dollar amount invested in the issuer's asset by each fund. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Issuer CDS is the time series of CDS prices extracted from Datastream. Breaking the Buck is the difference between $1 and the fund NAV excluding the sponsor support. Column (2) restrict attention to funds that have a NAV≥ 1. Column (3) exclude the funds that obtained support in the form of cash transfers or assets purchases by the sponsor institution: Columbia Variable Portfolio - MMF, Fifth Third Prime MMF/Instit, ING Money Market Fund, Wells Fargo Adv Heritage MMF, Sun Capital MMF, Morgan Stanley ILF, Northern MMF, Russell MMF, Schwab Cash Reserves, Schwab Money Market Fund, Schwab Retirement Advantage MF and T-Rowe Price Prime Reserve. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012.

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.8: Diversification Motive

	(1)	(2)	(3)	(4)	(5)	(6)
	Low Eurozone Exposure		High Eurozone Exposure			
Number of Ties$_{Aug\ 2011}$ × Post indicator $_{Oct\ 2011}$	0.0101***	189,968	0.00403***	396,440**	0.00490**	0.00316***
	(0.00235)	(156,176)	(0.00110)	(142,023)	(0.00206)	(0.00106)
Issuer CDS	-0.00283	-95,788	0.000770	68,343		-0.000646
	(0.00422)	(211,069)	(0.000582)	(101,918)		(0.00115)
Issuer CDS× Post indicator $_{Oct\ 2011}$	-0.00334***	-135,652	-0.00233***	-279,005***		-0.00145***
	(0.00114)	(147,553)	(0.000670)	(44,177)		(0.000500)
Fund Diversification $_{Aug\ 2011}$					0.0229*	
					(0.0125)	
Fund Diversification $_{Aug\ 2011}$× Post indicator $_{Oct\ 2011}$					-0.0298	
					(0.0195)	
Fund Share of Issuance						0.602
						(0.637)
Time fixed effects	✔	✔	✔	✔	✔	✔
Issuer fixed effects	✔	✔	✔	✔	✔	✔
Observations	2,276	2,276	2,532	2,532	4,808	4,153
R-squared	0.022	0.015	0.008	0.012	0.012	0.010

Notes: The dependent variable in columns (1), (3) and (5)-(6) is the change in the fraction of assets invested in the issuer's securities by each fund, whereas in columns (2) and (4) it is the change in the dollar amount invested in the issuer's asset by each fund. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Issuer CDS is the time series of CDS prices extracted from Datastream. Columns (1) and (2) restrict attention to funds that have below average exposure to the euro area in August 2011, while Columns (3) and (4) focus on funds with above average exposure to the euro area. Fund diversification is the number of different European issuers in the funds' portfolio over the sample period. Fund share issuance is the share of total securities issued by a single institution that is held by a given fund. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012.

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.9: The Effect of Market Liquidity

	(1) Δ % AUM Invested	(2) Δ % AUM Invested	(3) Δ % AUM Invested
Number of Ties$_{Aug\ 2011}$ × Post indicator$_{Oct\ 2011}$	0.00609*** (0.00188)	0.00632*** (0.00224)	0.00736** (0.00282)
Average Yield Issuer	-0.0441 (0.632)	-0.159 (0.498)	-0.154 (0.433)
Average Yield Issuer× Post indicator$_{Oct\ 2011}$		0.245 (0.462)	0.307 (0.414)
Average Maturity Issuer	0.00807 (0.00787)	0.00826 (0.00600)	0.00400 (0.00497)
Average Maturity Issuer × Post indicator$_{Oct\ 2011}$		0.000464 (0.00566)	-0.000818 (0.00525)
Issuance Size			0 (0)
Issuance Size × Post indicator$_{Oct\ 2011}$			-0* (0)
Time fixed effects	✔	✔	✔
Issuer fixed effects	✔	✔	✔
Observations	4,808	4,808	4,153
R-squared	0.010	0.010	0.009

Notes: The dependent variable is the change in the fraction of assets invested in the issuer's securities by each fund. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Average Maturity Issuer and Average Yield Issuer are the average maturity and yield of the securities issued by a given institution. Issuance size is the total dollar value of the securities issued by a given institution. Post indicator is a dummy variable that equals 1 after October, 2011. Robust standard errors clustered at the issuer level. The sample is a panel of monthly observations for money market mutual funds from August, 2011 to February, 2012.

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

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1.11 Appendix C - MMFs Trading Strategies

Table 1.10: Impact of Uncertainty on MMFs Exposure to Euro Area

	(1)	(2)	(3)	(4)	(5)	(6)
Post indicator	-4.619*** (0.879)					
Portfolio Liquidity	-0.0827*** (0.0255)	-0.0432* (0.0248)				
Portfolio Liquidity× Post indicator	0.0346** (0.0162)	0.0361** (0.0159)	0.0365** (0.0160)	0.0492** (0.0208)	0.0612*** (0.0216)	0.0422** (0.0190)
Controls		✔				
Time fixed effects		✔	✔	✔	✔	✔
Fund fixed effects			✔	✔	✔	✔
Fund characteristics				✔	✔	
Portfolio characteristics					✔	
Fund linear trends						✔
Observations	2,321	2,321	2,321	2,083	2,083	2,321
R-squared	0.043	0.071	0.072	0.054	0.072	0.393
Number of funds	331	331	331	331	331	331

Notes: This table reports the estimated effect of uncertainty on money market mutual fund (MMMF) holdings. The dependent variable is the exposure to the euro area for a given MMMF. The sample is a panel of monthly observations for taxable money market mutual funds from August, 2011 to February, 2012. *Post Indicator* is a dummy variable that equals 1 after October, 2011, when the VIX index spiked due to the European debt crisis. *Liquidity* is the fraction of assets maturing in the next 7 days computed as of August 2011. *Portfolio Liquidity* × *Post Indicator* is the interaction between the dummy variable and the fund portfolio liquidity. Fund characteristics include the fund yield, the size, and indicator variable if it is an institutional fund, the weighted average maturity, the pre-shock exposure to the euro area, and the net flow of assets. Portfolio characteristics include the fraction of assets invested in foreign bank obligations, repos, ABCP and Treasuries. Controls include the fund characteristics as measured in August 2011. Data on MMMF portfolios and yields are from iMoneyNet. Robust standard errors clustered by fund are reported in parentheses.

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.11: Impact of Uncertainty on MMFs Exposure to Euro Area

	(1)	(2)	(3)	(4)	(5)	(6)
Post indicator	1.468***					
	(0.450)					
Portfolio Liquidity	-0.0342*	-0.0349*				
	(0.0189)	(0.0189)				
Portfolio Liquidity× Post indicator	-0.0182*	-0.0183*	-0.0190*	-0.0196**	-0.0214**	-0.0281***
	(0.00962)	(0.00959)	(0.00973)	(0.00976)	(0.00986)	(0.00979)
Time fixed effects		✔	✔	✔	✔	✔
Fund fixed effects			✔	✔	✔	✔
Fund characteristics				✔	✔	
Portfolio characteristics					✔	
Fund linear trends						✔
Observations	2,084	2,084	2,084	2,082	2,082	2,084
R-squared	0.006	0.034	0.035	0.038	0.054	0.310
Number of funds	331	331	331	331	331	331

Notes: This table reports the estimated effect of uncertainty on money market mutual fund (MMMF) holdings. The dependent variable is the exposure to the euro area for a given MMMF. The sample is a panel of monthly observations for taxable money market mutual funds from October, 2011 to May, 2012. *Post Indicator* is a dummy variable that equals 1 after October, 2011, when the VIX index spiked due to the European debt crisis. *Liquidity* is the fraction of assets maturing in the next 7 days computed as of August 2011. *Portfolio Liquidity* × *Post Indicator* is the interaction between the dummy variable and the fund portfolio liquidity. Fund characteristics include the fund yield, the size, and indicator variable if it is an institutional fund, the weighted average maturity, the pre-shock exposure to the euro area, and the net flow of assets. Portfolio characteristics include the fraction of assets invested in foreign bank obligations, repos, ABCP and Treasuries. Controls include the fund characteristics as measured in August 2011. Data on MMMF portfolios and yields are from iMoneyNet. Robust standard errors clustered by fund are reported in parentheses.

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 1.12: Changes in MMFs Portfolio Liquidity

	(1) Short-Term Liquidity	(2) Short-Term Liquidity	(3) Short-Term Liquidity
Post indicator	5.485***		
	(1.107)		
Portfolio Liquidity	0.991***	0.991***	
	(0.00924)	(0.00920)	
Portfolio Liquidity × Post indicator	-0.109***	-0.110***	-0.114***
	(0.0208)	(0.0208)	(0.0215)
Time fixed effects		✔	✔
Fund fixed effects			✔
Observations	2,321	2,321	2,321
R-squared	0.023	0.035	0.035

Notes: The dependent variable is the fraction of assets maturing in the next seven days for a given MMMF. The sample is a panel of monthly observations for taxable money market mutual funds from August, 2011 to February, 2012. *Post Indicator* is a dummy variable that equals 1 after October, 2011, when the VIX index spiked due to the European debt crisis. *Liquidity* is the fraction of assets maturing in the next 7 days computed as of August 2011. *Portfolio Liquidity × Post Indicator* is the interaction between the dummy variable and the fund portfolio liquidity. Robust standard errors clustered by fund are reported in parentheses.

*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Chapter 2

Financial Disclosure and Market Transparency with Costly Information Processing

2.1 Introduction

Can the disclosure of financial information and the transparency of security markets be detrimental to issuers? One's immediate answer would clearly to be in the negative; financial disclosure should reduce adverse selection between asset issuers and investors. The same should apply to security market transparency: the more that is known about trades and quotes, the easier it is to detect the presence and gauge the strategies of informed traders, again reducing adverse selection. So both forms of transparency should raise issue prices and thus benefit issuers. If so, issuers should spontaneously commit to high disclosure and list their securities in transparent markets. This is hard to reconcile with the need for regulation aimed at augmenting issuers' disclosure and improving transparency in off-exchange markets. Yet, this is the purpose of much financial regulation – such as the 1964 Securities Acts Amendments, the 2002 Sarbanes-Oxley Act and the 2010 Dodd-Frank Act.[1]

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[1] For instance, Greenstone et al. (2006) document that when the 1964 Securities Acts Amendments extended disclosure requirements to OTC firms, these firms experienced abnormal excess returns of about 3.5 percent in the 10 post-announcement weeks. Similarly, several studies in the accounting literature document that tighter

In this paper we propose one solution to the puzzle: issuers do not necessarily gain from financial disclosure and market transparency if (i) it is costly to process financial information and (ii) not everyone is equally good at it. Under these assumptions, disclosing financial information may not be beneficial, because giving traders more information increases their information processing costs and thus accentuates the informational asymmetry between more sophisticated and less sophisticated investors, thus exacerbating adverse selection.

Specifically, we set out a simple model where the seller of an asset – e.g., an asset-backed security – searches for a buyer in a market with sequential trading. Before trading occurs, the issuer of the asset can disclose fundamental information about it, e.g. data about the asset's underlying pool of securities. If information is disclosed, investors must decide what weight to assign to it in judging its price implications, balancing the benefit to trading decisions against the cost of paying more attention. We show that when investors differ in processing ability, disclosure generates adverse selection: investors with limited processing ability will worry that if the asset has not already been bought by others, it could be because more sophisticated investors, who are better at understanding the price implications of new information, concluded that the asset is not worth buying. This depresses the price that unsophisticated investors are willing to pay; in turn the sophisticated investors, anticipating that the seller will have a hard time finding buyers among the unsophisticated, will offer a price below the no-disclosure level.

Hence, issuers may have good reason to reject disclosure, but they must weigh this concern against an opposite one: divulging information also helps investors avoid costly trading mistakes, and in this respect it stimulates their demand for the asset. Hence, issuers face a trade-off: on the one hand, disclosure attracts speculators to the market, since it enables them to exploit their superior information-processing ability and so triggers the pricing externality just described, to the detriment of issuers; on the other hand, it encourages demand from hedgers, because it protects them from massive errors in trading.

The decision discussed so far concerns the disclosure of information on cash flows via the release of accounting data, listing prospectuses, credit ratings, and so on. But in choosing the degree of disclosure, the issuer must also consider the transparency of the security market,

disclosure standards are associated with lower cost of capital and better access to finance for firms (see the survey by Leuz and Wysocki (2008)). ,

i.e. how much investors know about the trades of others. Market transparency amplifies the pricing externality triggered by financial disclosure, because it increases unsophisticated investors' awareness of the trading behavior of the sophisticated, and in this way fosters closer imitation of the latter by the former. In equilibrium, this increases the price concession that sophisticated investors require, and asset sellers will accordingly resist trading transparency. Hence, the interaction between financial disclosure and market transparency makes the two substitutes from the asset issuers' standpoint: they will be more willing to disclose information on cash flow if they can expect the trading process to be more opaque. The interaction between the two forms of transparency may even affect unsophisticated investors' willingness to trade: if market transparency increases beyond some critical point, financial disclosure might induce them to leave the market altogether, as they worry that the assets still available may have already been discarded by better-informed investors.

Hence, a key novelty of our setting is that it encompasses two notions of transparency that are generally analyzed separately by researchers in accounting and in market microstructure, even though they are naturally related: financial disclosure affects security prices, but the transparency of the trading process determines how and when the disclosed information is incorporated in market prices. We show that each of these two forms of transparency amplifies the other's impact on the security price. Interestingly, the recent financial crisis has brought both notions of transparency under the spotlight. The opacity of the structure and payoffs of structured debt securities – a form of low cash-flow transparency – is blamed for the persistent illiquidity of fixed-income markets. But the crisis has also highlighted the growing importance of off-exchange trading, with many financial derivatives (mortgage-backed securities, collateralized debt obligations, credit default swaps, etc.) traded in opaque over-the-counter (OTC) markets – an instance of low trading transparency.

Our model shows that the choice of transparency pits issuers against both sophisticated and unsophisticated investors, unlike most market microstructure models where it typically redistributes wealth from uninformed to informed investors. In our model, less financial disclosure prevents sophisticated investors from exploiting their processing ability and induces more trading mistakes by the unsophisticated, both because they have less fundamental information and because they cannot observe previous trades in order to update their beliefs about the asset's

value.

Besides providing new insights about the political economy of regulation, the model helps to address several pressing policy issues: if a regulator wants to maximize social welfare, how much information should be required when processing it is costly? When are the seller's incentives to disclose information aligned with the regulator's objective and when instead should regulation compel disclosure? How does mandatory disclosure compare with a policy that prohibits unsophisticated investors from buying complex securities?

First, we show that in general there can be either over- or under-provision of information, depending on processing costs and the seller's bargaining power. Surprisingly, there is a region in which the seller has a greater incentive than the regulator for disclosure. This occurs when enough unsophisticated investors are in the market and the expected value of the asset is low: sellers will spontaneously release more information when their assets are not much sought-after. This is also more likely when the seller appropriates a large part of the expected trading gains.

When instead there are many sophisticated investors, issuers fear their superior processing ability and therefore inefficiently prefer not to disclose. Hence, regulatory intervention for disclosure is required. This is likely to occur in markets for complex securities, such as asset-backed securities, where sophistication is required to understand the asset's structure and risk implications, so that sophisticated investors are attracted. This is less likely to be the case for plain-vanilla assets such as treasuries or corporate bonds, where sophisticated investors cannot hope to exploit their superior processing ability.

Finally, we show that in markets where most investors are unsophisticated, it may be optimal for the regulator to license market access only to the few sophisticated investors present, as this saves the processing costs that unsophisticated investors would otherwise bear. Thus, when information is difficult to digest, as in the case of complex securities, the planner should allow placement only with the "smart money", not to all comers.

These insights build on the idea that not all the information disclosed to investors is easily and uniformly digested – a distinction that appears to be increasingly central to regulators' concerns. For instance, in the U.S. there is controversy about the effects of Regulation Fair Disclosure promulgated in 2000, which prohibits firms from disclosing information selectively to analysts and shareholders: according to Bushee et al. (2004), "Reg FD will result in firms

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disclosing less high-quality information for fear that [...] individual investors will misinterpret the information provided".[2] Similar concerns lie behind the current proposals to end quarterly reporting obligations for listed companies in the revision of the EU Transparency Directive: in John Kay's words, "the time has come to admit that there is such a thing as too much transparency. The imposition of quarterly reporting of listed European companies five years ago has done little but confuse and distract management and investors" (Kay (2012)). In the same spirit, U.S. regulation is now seeking to mitigate the demanding disclosure requirements of the Sarbanes-Oxley Act: the 2012 Jumpstart Our Business Startups (JOBS) Act reduces the accounting and security market transparency requirements for new public companies, lifting the threshold for SEC registration from 500 to 2,000 shareholders and allowing smaller companies to use internet portals to obtain "crowd funding" with minimal reporting obligations.

The rest of the paper is organized as follows. Section 2.2 places it in the context of the literature. Section 2.3 presents the model. Section 2.4 derives the equilibrium under the assumption of complete transparency of the security market. Section 2.5 relaxes this assumption and explores the interaction between financial disclosure and market transparency. Section 2.6 investigates to the role of regulation, and Section 2.7 concludes.

2.2 Related literature

This paper is part of a growing literature on costly information processing, initiated by Sims (2003) and Sims (2006), which argues that agents are unable to process all the information available, and accordingly underreact to news. Subsequent work by Peng and Xiong (2006), Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010) and Woodford (2005) brought out the implications of information constraints for portfolio choice problems and monetary policy.[3] While in these papers limited cognition stems from information capacity

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[2]Bushee et al. (2004) find that firms that used closed conference calls for information disclosure prior to the adoption of Reg FD were significantly more reluctant to do so afterwards. In surveys of analysts conducted by the Association of Investment Management and Research, and the Security Industry Association, 57% and 72% of respondents respectively felt that less substantive information was disclosed by firms in the months following the adoption of Reg FD. Gomes et al. (2007) find a post-Reg FD increase in the cost of capital for smaller firms and firms with a greater need to communicate complex information (proxied by intangible assets).

[3]See also Hirshleifer and Teoh (2003) who analyze firms' choice between alternative methods for presenting information and the effects on market prices, when investors have limited attention.

constraints, in our setting it arises from the cost of increasing the precision of information.

The idea that information processing is costly squares with a large body of empirical evidence, as witnessed by surveys of studies in psychology (Pashler and Johnston (1998) and Yantis (1998)), in experimental research on financial information processing (Libby et al. (2002) and Maines (1995)), and in asset pricing (Daniel et al. (2002)).[4] In particular, there is evidence that limited attention affects portfolio choices: Christelis et al. (2010) investigate the relationship between household portfolio composition in 11 European countries and indicators of cognitive skills drawn from the Survey of Health, Ageing and Retirement in Europe (SHARE), and find that the propensity to invest in stocks is positively associated with cognitive skills and is driven by information constraints, not preferences or psychological traits.[5] Moreover, investors appear to respond quickly to the more salient data, at the expense of other price-relevant information (see for instance Huberman and Regev (2001), Barber and Odean (2008), and DellaVigna and Pollet (2009)). Investors' limited attention can result in slow adjustment of asset prices to new information, and thus in return predictability: the delay in price response is particularly long for conglomerates, which are harder to value than standalone firms and whose returns can accordingly be predicted by those of the latter (Cohen and Lou (2011)).

Several recent papers show that investors may overinvest in information acquisition. For instance, in Glode et al. (2011) traders inefficiently acquire information as more expertise improves their bargaining positions. In Bolton et al. (2011a), too many workers choose to become financiers compared to the social optimum, due the rents that informed financiers can extract from entrepreneurs by cream-skimming the best deals. In these papers, the focus is on the acquisition of information. Our focus is instead on information processing, and its effects on the issuers' incentive for disclosure information in the first place.

Several authors have suggested possible reasons why limiting disclosure may be efficient, starting with the well-known argument by Hirshleifer (1971) that revealing information may destroy insurance opportunities. The detrimental effect of disclosure has been shown in settings

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[4] See Carlin (2009) for a model of strategic complexity, and Gennaioli and Shleifer (2010) and Gennaioli et al. (2011) for studies of different investors' behavioral limitations in processing information.

[5] The accounting literature too sees a discrepancy between the information released to the market and the information digested by market participants: Barth et al. (2003) and Espahbodi et al. (2002), among others, distinguish between the disclosure and the recognition of information, and observe that the latter has a stronger empirical impact, presumably reflecting better understanding of the information.

where it can exacerbate externalities among market participants, as in our setting: Morris and Shin (2011) analyze a coordination game among differentially informed traders with approximate common knowledge; Vives (2011) proposes a model of crises with strategic complementarity between investors and shows that issuing a public signal about weak fundamentals may backfire, aggravating the fragility of financial intermediaries. In our model too, disclosure creates trading externalities and strategic behavior, which are exacerbated by transparency about the trading process; but as disclosure is decided by issuers, this may produce an inefficiently low level of transparency.

Our result that issuers may be damaged by financial disclosure parallels Pagano and Volpin (2010), who show that when investors have different information processing costs, transparency exposes the unsophisticated to a winners' curse at the issue stage: to avoid the implied underpricing, issuers prefer opacity. But opting for an opaque primary market may generate an illiquid secondary market, if the information not divulged is later discovered by secondary market traders; if this illiquidity generates negative externalities, it may be socially efficient to require disclosure. Our present setting shares with Pagano and Volpin (2010) the idea that disclosure may aggravate adverse selection if investors have different information processing ability, but we differ in other important respects. First, here we show that issuers do not always opt for opacity, since they will trade off the costs of disclosure (investors' information processing costs and the strategic interaction among them) against its benefits (contribution to avoiding mistaken portfolio choices). Moreover, unlike Pagano and Volpin (2010), this paper shows that the level of disclosure chosen by issuers may either exceed or fall short of the socially efficient level, and is also affected by the degree of trading transparency.[6]

Another model in which issuers may choose an inefficiently low level of disclosure is Fishman and Hagerty (2003). In their setting, some customers fail to grasp the meaning of the information disclosed by the seller, seeing only whether or not the seller discloses a signal or not. They show that if the fraction of sophisticated customers is too small, voluntary disclosure will not occur, and mandatory disclosure benefits informed customers and harms the seller. They conclude that in markets where information is difficult to understand disclosure should

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[6]Recently, Dang et al. (2010) and Yang (2012) have also noted that opacity may be beneficial insofar as it reduces informational asymmetries, but they mainly concentrate on the security design implications of this insight.

be mandatory. We find opposite results: a small fraction of speculators encourages the seller to disclose information, since it is associated with less adverse selection. Moreover, regulators are less likely to require disclosure in markets where information is hard to understand, since they realize that unsophisticated investors must spend resources to understand it: hence, if their information-processing costs are large, the regulator may prefer to save these costs by not requiring disclosure or, better, by restricting investment in complex assets to sophisticated investors.

In practice, issuers may want to refrain from disclosing information for other reasons as well. First, disclosure may be deterred by the costs of credibly transmitting information to investors (listing fees, auditing fees, regulation compliance costs, etc.). A second, less obvious cost arises from the non-exclusive nature of disclosure: information to investors is disclosed simultaneously to competitors, who may then exploit it to appropriate the firm's profit opportunities, as noted by Campbell (1979) and Yosha (1995). A third cost arises from the company's lesser ability to evade or elude taxes: the more detailed accounting information for investors naturally goes also to the tax authorities, and the implied additional tax burden may induce them to limit disclosure (see Ellul et al. (2012)).

2.3   The model

The issuer of an indivisible asset wants to sell it to investors: he might be the issuer of a new asset-backed security (ABS), a firm looking to offload its risk exposure to interest rates or commodity prices, or a household seeking a buyer for its house. The issuer entrusts the sale of the asset to a dealer, who sells it through a search market that randomly matches him with buyers. Before the trade, the issuer can disclose a noisy signal about the value of the asset. For instance, the issuer of an ABS can choose between a registered securitization, which requires detailed disclosures in the issuance process, and Rule 144a, which exempts the issuer from these disclosure requirements. To understand the pricing implications, potential buyers must devote some attention to analyzing the signal. But investors face different costs: understanding financial news is more costly for unsophisticated investors than for professionals with expertise, better equipment and more time. Unsophisticated investors may still want

to buy for non-informational reasons, such as to hedge some risk (these we accordingly call "hedgers"). By contrast, sophisticated investors are assumed to trade purely to exploit their superior information-processing ability, and are accordingly labeled "speculators".

We posit two equally likely states of the world: in the good state, the asset's value v equals v_g, in the bad, v_b, where $v_b < 0 < v_g$. The unconditional mean of the value is $v^e \equiv (v_g + v_b)/2$.[7] The issuer can disclose a signal $\sigma \in \{v_b, v_g\}$ correlated with the value of the security. If he does, before trading investor i must decide the level of attention $a \in [0, 1]$ devoted to this signal, which increases the probability of correctly estimating the probability distribution of the value: $\Pr(\sigma = v|v) = \frac{1+a_i}{2}$. So by paying more attention, investors read the signal more accurately. The choice of a captures the investors' effort to understand, say, the risk characteristics of a new ABS based on the data disclosed by its issuer about the underlying asset pool.

However, greater precision comes at an increasing cost: the cost of information processing is $C_i(a, \theta)$, with $\partial C_i/\partial a > 0$ and $\partial^2 C_i/\partial a^2 > 0$, where the shift parameter θ_i measures inefficiency in processing, i.e. the investor's "financial illiteracy".[8] To simplify the analysis, we posit a quadratic cost function: $C_i(a, \theta) = \theta_i a^2/2$. The greater θ_i, the harder for investor i to measure the asset's price sensitivity to factors like interest rates, commodity and housing price changes, possibly because of its complexity: as the recent financial crisis has made apparent, understanding the price implications of a CDO's structure requires considerable skills and substantial resources. Information processing costs differ across investors: some are unsophisticated "hedgers" ($i = h$), whose cost is $\theta_h = \theta$; others are sophisticated "speculators" ($i = s$) who face no such costs: $\theta_s = 0$.[9]

Trading is via a matching and bargaining protocol: with probability μ, the dealer entrusted with the sale (henceforth, "seller") is initially matched with a hedger; with probability $1 - \mu$, with a speculator. If the initial match produces no trade, the seller is contacted by the other type of investor.[10] The parameter $1 - \mu$ can be interpreted as the fraction of speculators in

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[7] This binary distribution is assumed just to simplify the exposition, but the results are qualitatively the same with a continuum of possible asset's values.

[8] Like Tirole (2009), we do not assume bounded rationality: in Tirole's framework information-processing costs rationally lead to incomplete contracts, which impose costs on the parties. Similarly, in our setting unsophisticated investors decide how much information they wish to process rationally, in the awareness that a low level of attention may lead to mistakes in trading.

[9] The model easily generalizes to the case where speculators too have positive information-processing costs or where there are more than two types of investors.

[10] This assumption is with no loss of generality: if the seller were contacted again by an investor of the same

the population of investors: if investors are randomly drawn from a common distribution, in a securities market that attracts more speculators, one of them is more likely to deal with the issuer.

Each investor i has a reservation value $\omega_i > 0$, independent of v and the net value from purchasing the asset for investor i is $v - \omega_i$. The seller places no value on the asset and is uninformed about v. This allows us to focus on the endogenous information asymmetry among investors and, although the information structure described here is not essential for our results, it greatly simplifies their exposition. Once the seller is matched with a buyer, they negotiate a price and the trade occurs whenever the buyer expects to gain a surplus: $E(v - \omega_i \mid \Omega_i) > 0$, where Ω_i is buyer i's information set. The seller makes a take-it-or-leave-it offer with probability β_i.

The outcome of bargaining is given by the generalized Nash solution under symmetric information: the trade occurs at a price such that the seller captures a fraction β_i and the investor a fraction $1 - \beta_i$ of this expected surplus, where β_i measures the seller's bargaining power.[11] As in the search-cum-bargaining model of Duffie et al. (2005), the seller can observe the investor's type. Real-world examples of such a setting are OTC and housing markets, where matching via search gives rise to a bilateral monopoly at the time of a transaction.

We impose the following restrictions on the parameters:

Assumption 1 $\omega_s = v^e > \omega_h > 0$.

Hence, the two types of investors differ in their outside options. Hedgers have a comparatively low outside option, and therefore view the asset as a good investment on average $(v^e > \omega_h > 0)$. Say, they are farmers who see the asset as a hedge against crop's price risk. In contrast, speculators are in the market only to exploit their information processing ability, because they have no intrinsic need to invest in the asset: $\omega_s = v^e$. For example, they may be hedge funds or investment banks with strong quant teams.

Assumption 2 $\theta > (1 - \beta_h)(1 - \beta_s)(v_g - v_b)/4$.

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type, the new match naturally again produces no trade: since investors of the same type are identical. Only a new match with an investor of the other type could produce a trade.

[11] The assumption that bargaining occurs under symmetric information is discussed in detail at the end of this section.

This assumption on θ implies that the hedgers' information processing cost is high enough to deter them from achieving perfectly precise information; that is, they will choose an optimal attention level $a_h^* < 1$. Otherwise, in equilibrium hedgers would have the same information as speculators ($\Omega_h = \Omega_s$).

The two types of investor may also differ in bargaining power: the seller captures a fraction β_h of the expected gains from trade when dealing with hedgers, but potentially a smaller fraction $\beta_s \leq \beta_h$ when dealing with speculators, who are better at shopping around for the best deals and obtaining price concessions as part of a stable trading relationship.

In the baseline version analyzed in the next section, the timeline of the game is as follows:

1. The issuer decides whether or not to disclose the signal, i.e. $d \in \{0, 1\}$.

2. Investor i is randomly matched with the seller: with probability μ, he is type h and with probability $1 - \mu$, type s.

3. Investor i chooses his attention level a_i and forms his expectation of the asset value $\widehat{v}_i(a_i, \sigma)$.

4. If he decides to buy, buyer and seller bargain over the expected surplus.

5. If he does not buy, the other investor, upon observing the outcome of stage 4, is randomly matched to the seller and bargains with him over the expected surplus.

This means that in this baseline version, the final stage of the game posits complete market transparency, previous trades being observable to all market participants. In Section 2.5 we relax this assumption, and allow investors to fail to observe previous trades: this enables us to explore how less trading transparency affects the equilibrium outcome.

2.3.1 Discussion

We now discuss the main assumptions of the model.

First, we posit that investors choose their level of attention after matching with the seller: they do not analyze a security's prospectus, say, until they have found a security available for purchase. The alternative is to assume that buyers make their information inquiries in advance,

before matching. But this entails greater costs for investors, who would sustain information-processing costs even for securities that they do not buy: so if given the choice they would opt for the sequence we assume.

Second, there is the possibility that the seller might commit to trade only with hedgers. This would allow him to disclose information without attracting the speculators. However, the externality posited arises from simply receiving an offer from a speculator, not trading with him: even if the seller excluded trading with speculators, he could not avoid receiving offers from them. This is sufficient to induce learning by hedgers and hence generate the externality present in the model.

Third, the issuer is assumed not to condition his disclosure policy upon the signal of the asset's cash flow. This assumption is not essential, however: for instance, if the issuer were to release the signal only if good ($\sigma = v_g$), investors would infer that the signal is bad when not released. A similar unraveling argument shows that any other disclosure policy conditional on the signal is equivalent to our assumed policy ($d = 1$), as in Grossman (1981) and Milgrom (1981). Moreover, this policy captures situations in which the issuer does not know which signal value will increase the investors' valuation of the asset, perhaps because investors' trading motives or risk exposures are not known.

Fourth, we take the dealer who sells the asset to be uninformed about its value. In this case, the assumption that bargaining occurs under symmetric information is without loss of generality.[12] If the seller is matched with a speculator, who in equilibrium perfectly infers the asset value from the signal and gains from trade only if $v = v_g$, the seller can infer this information from the speculator's willingness to buy. Similarly, if the seller is matched with a hedger who is willing to buy the asset, he can infer the hedger's posterior belief about the asset's value (since he knows the parameters of the hedger's attention allocation problem, and therefore can infer the attention chosen by the hedger). Hence, the gains from trade between seller and hedger are common knowledge, so that in this case too bargaining occurs under symmetric information. This is the same reasoning offered by Duffie et al. (2005) to justify the adoption of the Nash bargaining solution in their matching model. In section 2.5, where we allow for an opaque market, we assume that the least informed agent makes an ultimatum

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[12] In the appendix we provide a discussion of how the results would change with different bargaining protocols.

offer when trading. This allows us to convey our main intuition in a simple manner, without needing equilibrium refinement to solve a signaling game between seller and buyer.

2.4 Equilibrium

We solve the game backwards to identify the subgame perfect equilibrium, that is, the strategy profile (d, a_s, a_h, p_s, p_h) such that (i) the disclosure policy d maximizes the seller's expected profits; (ii) the choice of attention a_i maximizes the typical buyer $i's$ expected gains from trade; (iii) the prices p_s bid by speculators and p_h bid by hedgers solve the bargaining problem specified above. Specifically, each type of investor pays a different price depending on the disclosure regime, and possibly on whether he is matched with the seller at stage 4 (when he is the first bidder) or 5 (when he bids after another investor elected not to buy). Each of the following sections addresses one of these decision problems.

2.4.1 The bargaining stage

When the seller bargains with an investor i, his outside option $\bar{\omega}_i$ is endogenously determined by the other investors' equilibrium behavior. The price p_h agreed by hedgers solves the following program:

$$p_h \in \arg\max (p_h - \bar{\omega}_h)^{\beta_h} (\widehat{v}(a, \sigma) - p_h - \omega_h)^{1-\beta_h} . \tag{2.1}$$

The first term in this expression is the seller's surplus: the difference between the price that he obtains from the sale and his outside option $\bar{\omega}_h$, which is the price the hedger expects a speculator to offer if the trade does not go through. The second term is the buyer's surplus: the difference between the hedger's expected value of asset $\widehat{v}$ over and above the price paid to the seller, and his outside option ω_h.

The expected value from the hedger's standpoint, as a function of his choice of attention a and of the signal σ, is

$$\widehat{v}(a, \sigma) \equiv \mathbb{E}[v|\sigma] = \begin{cases} \frac{1+a}{2}v_g + \frac{1-a}{2}v_b & \text{if } \sigma = v_g, \\ \frac{1-a}{2}v_g + \frac{1+a}{2}v_b & \text{if } \sigma = v_b, \end{cases}$$

where $\frac{1+a}{2}$ is the probability that the signal is correct (and $\frac{1-a}{2}$ the complementary probability

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that it is not). This probability is an increasing function of the attention a that hedgers pay to the signal: in the limiting case $a = 0$, their estimate would be the unconditional average v^e, whereas in the polar opposite case $a = 1$, their estimate would be perfectly precise. In what follows, we conjecture that speculators, who have no information processing costs, will choose $a_s^* = 1$, while hedgers choose a lower attention level $a_h^* \in [0,1)$.[13] Thus, in equilibrium speculators know the value of the asset and hedgers hold a belief $\widehat{v}(a, \sigma)$ whose precision depends on the attention level they choose.

Symmetrically, the price offered by speculators solves the following bargaining problem:

$$ p_s \in \arg\max \left(p_s - \bar{\omega}_s\right)^{\beta_s} \left(v - \omega_s - p_s\right)^{1 - \beta_s}, \tag{2.2} $$

where $\bar{\omega}_s$ is the price that will be offered by hedgers if speculators do not buy.

By solving problems (2.1) and (2.2), we can characterize the solution to the bargaining problem:

Proposition 14 (Bargaining outcome) *Suppose that the signal is disclosed at stage 1. Then if at stage 2 the seller is initially matched with the speculator and the trade fails to occur, the hedger will subsequently refuse to buy. If instead the seller is initially matched with the hedger and the trade fails to occur, the seller will subsequently trade with the speculator. The prices at which trade occurs with the two types of investor are*

$$ p_h^d = \beta_h \left(\widehat{v}(a_h, v_g) - \omega_h\right) + (1 - \beta_h) p_s^d \frac{1 + a_h}{2} \text{ and } p_s^d = \beta_s \left(v_g - \omega_s\right). \tag{2.3} $$

If instead the signal is not disclosed at stage 1, the trade occurs only with the hedger at the price

$$ p_h^{nd} = \beta_h \left(v^e - \omega_h\right). \tag{2.4} $$

When the signal is disclosed ($d = 1$), an initial match with the speculator leads to trade only if the asset value is high, because the speculator's reservation value ω_s exceeds the low realization v_b. Therefore, upon observing that the speculator did not buy the hedger will revise his value estimate down to v_b. Since this value falls short of his own reservation value (as

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[13] In the next section we solve the attention allocation problem and show that this conjecture is correct.

$v_b < 0 < \omega_h$), he too will be unwilling to buy, so the seller's outside option is zero: $\bar{\omega}_s = 0$. This information externality weakens the seller's initial bargaining position vis-à-vis the speculator, by producing a lower outside option than when the hedger comes first (and so is more optimistic about the asset value, his estimate being $\hat{v}(a_h, v_g) > v_b$).

What hedgers infer from speculators' decisions in our model is reminiscent of the results in the literature on herding (Scharfstein and Stein (1990) and Banerjee (1992)). In our case, however, the hedger always benefits from observing speculators' decisions, because his "herding" involves no loss of valuable private information. By contrast, the speculator does not learn from the hedger's behavior: since in equilibrium he has better information, he draws no value inference upon seeing that the hedger does not buy.

As we show below, in equilibrium the hedger buys only when he is the first to be matched, and only upon receiving good news. Hence, the price p_h at which he trades according to expression (2.3) is his expected surplus conditional on good news: the first term is the fraction of the hedger's surplus captured by the seller when he makes the take-it-or-leave-it offer; the second term is the fraction of the seller's outside option p_s that the hedger must pay when he makes the take-it-or-leave-it offer. This outside option is weighted by the probability $\frac{1+a_h}{2}$ that the hedger attaches to the asset value being high, and therefore is increasing in the hedger's level of attention a_h.

By contrast, the price offered by the speculator is affected only by his own bargaining power: he captures a share $1 - \beta_s$ of the surplus conditional on good news. This is because when he bargains with the speculator, the seller's outside option is zero: if he does not sell to him, the asset goes unsold, as the hedger too will refuse to buy.

It is important to see that the price concession that speculators obtain as a result of hedgers' emulation depends on the hedgers' awareness of the speculators' superior information-processing ability, which exposes hedgers to a "winner's curse". But this adverse selection effect itself depends on the seller's initial public information release, since without it speculators would lack the very opportunity to exploit their information-processing advantage.

Indeed, if there is no signal disclosure ($d = 0$), the speculator will be willing to buy the asset only at a zero price, because when matched with the seller his expected gain from trade would be nil: $v^e - \omega_s = 0$. This is because in this case he cannot engage in information processing,

which is his only rationale for trading. By the same token, absent both the signal and the implicit winner's curse, the hedger will value the asset at its unconditional expected value v^e, and will always be willing to buy it at a price that leaves the seller with a fraction β_h of his surplus $v^e - \omega_h$.

2.4.2 Attention allocation

So far we have taken investors' choice of attention as given. Now we characterize it as a function of their processing ability. Investors process the signal σ to guard against two possible types of errors. First, they might buy the asset when its value is lower than the outside option: if so, by investing attention a they save the cost $|v_b - \omega_i|$. Second, they may fail to buy the asset when it is worth buying, i.e. when its value exceeds their outside option ω_i: in this case, not buying means forgoing the trading surplus $v_g - \omega_i$.

In principle there are four different outcomes: the hedger may (i) never buy, (ii) always buy, irrespective of the signal realization; (iii) buy only when the signal is v_g or (iv) buy only when the signal is v_b. Proposition 2 characterizes the optimal choice of attention allocation and shows that hedgers find it profitable to buy if and only if the realized signal is v_g, that is, if the seller discloses "good news".

Investors choose their attention level a_i to maximize expected utility:

$$\max_{a_i \in [0,1]} (1 - \beta_i) \left(\frac{1 + a_i}{2} v_g + \frac{1 - a_i}{2} v_b - \omega_i - \bar{\omega}_i(a_i) \right) - \theta_i \frac{a_i^2}{2}, \text{ for } i \in \{h, s\}, \qquad (2.5)$$

which shows that the seller's outside option is a function of the attention choice. The solution to problem (2.5) is characterized as follows:

Proposition 15 (Choice of attention) *The speculator's optimal attention is the maximal level $a_s^* = 1$. The hedger's optimal attention is*

$$a_h^* = \frac{1 - \beta_h}{4\theta} \left(1 - \frac{\beta_s}{2} \right) (v_g - v_b),$$

which is decreasing in financial illiteracy θ and in the seller's bargaining power β_h and β_s, and increasing in the asset's volatility $v_g - v_b$. The hedger buys the asset if and only if the realized

signal is v_g when the asset's volatility is sufficiently high. Otherwise, the hedger chooses $a_h^* = 0$ and always buys the asset.

The first part of the proposition captures the speculator's optimal choice of attention, which confirms the conjecture made in deriving the bargaining solution: as he has no processing costs, the speculator chooses the highest level of attention, and therefore extracts the true value of the asset.

The second part characterizes the choice of attention by hedgers, for whom processing the signal is costly. First, their optimal choice is an interior solution, due to Assumption 2. And, when the seller extracts a larger fraction of the gains from the trade (i.e. β_h is large), the hedger spends less on analyzing the information, because he expects to capture a smaller fraction of the gains from trade. Moreover, the optimal choice a_h^* is increasing in the range of values that the asset can take, because a larger range $v_g - v_b$ increases the magnitude of the two types of errors that the hedger must guard against.

As one would expect, the hedger's optimal attention a_h^* is decreasing in his financial illiteracy θ, because the greater the cost of analyzing the signal σ, the less worthwhile it is to do so. Alternatively, one can interpret θ as a measure of the informational complexity of the asset (the pricing implications of information being harder to grasp for asset-backed securities than for plain-vanilla bonds).

The comparative-statics result on β_s is less immediate, and follows from the sequential bargaining structure of our model. When the seller has high bargaining power β_s vis-à-vis the speculator, the hedger chooses a lower attention level: the informational rent the seller must pay to the speculator is lower, so he is less eager to sell to the hedger; this reduces the hedger's trading surplus, hence his incentive to exert attention.

Finally, the hedger allocates positive attention a_h^* to process the signal only if it is positive and the asset's volatility $v_g - v_b$ is sufficiently great. Intuitively, if $v_g - v_b$ is low, it is optimal to save the processing costs and buy regardless of the information disclosed. In what follows we focus on the more interesting case in which it is optimal for the hedger to buy the asset only when he gets a positive signal about the asset value.

2.4.3 Disclosure policy

To determine what incentive the issuer has to disclose the signal σ, we must compare the expected profits obtained from the sale of the asset in the two different disclosure regimes, building on the foregoing analysis. In the no-disclosure regime, the seller's expected profit is simply

$$\mathbb{E}\left[\pi^{nd}\right] = p_h^{nd} = \beta_h\left(v^e - \omega_h\right), \tag{2.6}$$

because, as we have shown, the speculator does not buy when $d = 0$.

Under disclosure, however, the seller is matched with the hedger with probability μ, so that his expected profit is $E\left[\pi_h^d\right]$, whereas with probability $1 - \mu$ he is matched with the speculator and has expected profit of $E\left[\pi_s^d\right]$. Hence on average the seller's profit is

$$\mathbb{E}\left[\pi^d\right] = \mu\mathbb{E}\left[\pi_h^d\right] + (1 - \mu)\mathbb{E}\left[\pi_s^d\right]. \tag{2.7}$$

Let us consider the two terms in this expression. The first refers to the case in which the seller first meets the hedger, and is equal to

$$\mathbb{E}\left[\pi_h^d\right] = \frac{1 + a_h^*}{4}p_h^d + \frac{1 - a_h^*}{4}p_s^d, \tag{2.8}$$

where p_h^d and p_s^d are the equilibrium prices defined by Proposition 1. With probability $(1 + a_h^*)/4$ the value of the asset is v_g and the hedger observes a congruent signal v_g, the probability a_h^* being defined by Proposition 2. In this case, the hedger finds it profitable to buy the asset at the price p_h^d. With probability $(1 - a_h^*)/4$, instead, the asset's value is v_g but the signal received by the hedger is v_b, in which case he does not trade, so the asset ends up being bought by the speculator at price p_s^d.

If the seller is matched with the speculator, his expected profit is

$$\mathbb{E}\left[\pi_s^d\right] = \frac{1}{2}p_s^d. \tag{2.9}$$

In this case, with probability $1/2$ the signal tells the speculator that the asset's value is higher than his outside option, so that he is willing to trade at the price p_s. With complementary

probability $1/2$ the value turns out to be v_b, which induces both the speculator and the hedger to refrain from trading (for the hedger this reflects a negative inference from seeing that speculator does not buy).

Using expressions (2.8) and (2.9), the expression (2.7) for the seller's expected profits under disclosure becomes:

$$\mathbb{E}\left[\pi^d\right] = \mu\frac{1 + a_h^*}{4}(p_h^d - p_s^d) + \frac{1}{2}p_s^d. \tag{2.10}$$

To choose between disclosure ($d = 1$) and no disclosure ($d = 0$), the seller compares the expected profits (2.10) and (2.6) in the two regimes, evaluated at the equilibrium prices defined by Proposition 1. Using this comparison we can characterize the issuer's incentive to disclose information:

Proposition 16 (Choice of financial disclosure) *The issuer's net benefit from disclosing the signal σ is increasing in the fraction μ of hedgers and in the asset's volatility $v_g - v_b$ and decreasing in the hedgers' financial illiteracy θ.*

To intuit the reason for these results, consider that in this model financial disclosure has both costs and benefits for the issuer. The cost consists in the fact that disclosure enables speculators to deploy their information-processing skills, triggering an information externality that depresses the price. The benefits are twofold: first, disclosure induces hedgers to invest attention in the valuation of the asset and thereby enhances their willingness to pay for it (as can be seen by comparing p_h^d in (2.3) to p_h^{nd} in (2.4)); second, it increases the speculator's willingness to pay in good states of the world.

The cost arises with probability $1 - \mu$, which is the likelihood of the seller being matched initially with the speculator. Conversely, the higher the chance μ of trading immediately with the hedger, the less the seller worries that disclosure may trigger the informational externality: this explains why the issuer's willingness to disclose is increasing in μ.

The benefits of disclosure for the seller are increasing in the asset's volatility: first, a more volatile asset induces the hedger to pay more attention to its valuation (Proposition 2), which increases the price p_h^d he is willing to pay (from expression (2.3)); second, volatility increases the surplus that the seller can extract, under disclosure, from trading with the speculator, because it increases the latter's willingness to pay in the good state.

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The comparative statics are summarized in Figure 1: the issuer opts for disclosure in the region where the fraction μ of hedgers is high and/or volatility $v_g - v_b$ is high.
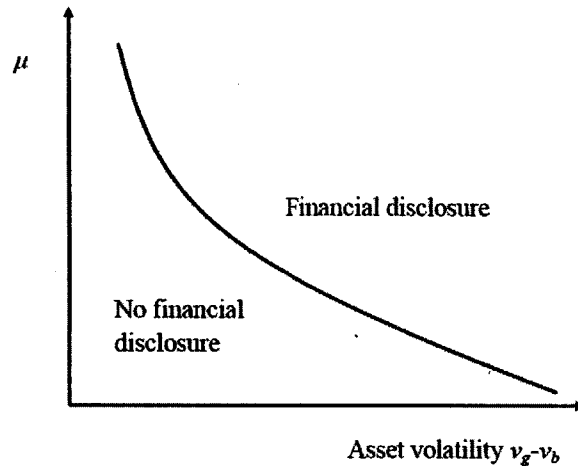

Figure 2-1: Seller's disclosure policy

Proposition 3 also highlights that the issuer is less inclined to disclosure when the parameter θ is high, i.e. when the financial literacy of investors is low and/or the asset is complex, as in these circumstances the issuer anticipates that disclosure will fail to elicit a high level of attention by investors and accordingly not raise their valuation of the asset significantly.

2.5 The effect of market transparency

In analyzing issuers' choice of disclosure, so far we have assumed that the market is fully transparent; that is, that subsequent buyers perfectly observe whether a previous trade has occurred or failed. This need not always be the case however: securities markets differ in their post-trade transparency, the extent to which information on previous trades is disseminated to actual and potential participants.[14] Accordingly, we now generalize to examine how the results are affected by less than perfect market transparency. We now assume that at stage 5 players

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[14]For empirical studies on the effect of post-trade transparency on market quality see Naik et al. (1994), Gemmill (1996), Board and Sutcliffe (1995), and Saporta et al. (1999) which analyze the effects of delayed trade reporting on the London Stock Exchange, whereas Porter and Weaver (1998) examine delayed reporting on the Nasdaq Stock Market.

observe the outcome of the match that occurred at stage 4 only with probability γ. Hence the parameter γ can be taken as a measure of transparency, and conversely $1 - \gamma$ as a measure of opacity.

In this model, market opacity attenuates the information externality between speculators and hedgers: the less likely hedgers are to know whether a previous match between seller and speculator failed, the less frequently they themselves will refrain from buying, thus depressing the price. In turn, since speculators' failure to buy may go unobserved by hedgers, they will be able to obtain less of a price concession. Hence, greater market opacity (lower γ) enables the seller to get a higher price.

However, opacity also has a more subtle – and potentially countervailing – effect: even if the hedger does not observe that a previous match has failed to result in a trade, he might still suspect that such a match did occur, and that he should accordingly refrain from buying. If the market is very opaque (γ very low), this suspicion may lead the hedger to withdraw from the market entirely: in other words, market opacity may generate a "lemons problem". Hence, we shall see that, although opacity attenuates information externalities between traders, if it becomes too extreme it may lead to a market freeze. The latter result is closer than the former to typical market microstructure models.

Let us analyze the first effect in isolation, taking the hedger's participation and pricing decision as given. Suppose the issuer discloses the signal σ at stage 1 and is matched with a speculator at stage 4. If the market is opaque, the seller might be able to place the asset even if bargaining with the speculator broke down, since the hedger might still be willing to buy. Hence, the speculator must offer a price that compensates the seller for this outside option, which did not exist under full transparency ($\gamma = 1$) as the hedger is never willing to buy the asset when he comes second. Specifically, if $\gamma < 1$, the opaque-market price $p_s^o(\gamma)$ at which the speculator will buy is a weighted average of his surplus $v_g - \omega_s$ and the seller's outside option, i.e. the price p_h^o the hedger is willing to pay in the opaque market when he fails to see the previous match (which occurs with probability $1 - \gamma$) and believes that the asset has high value (which occurs with probability $\frac{1+a_h}{2}$):

$$p_s^o(\gamma) = \beta_s(v_g - \omega_s) + (1 - \beta_s)(1 - \gamma)\frac{1 + a_h}{2}p_h^o. \qquad (2.11)$$

This expression shows that speculators' offer is decreasing in market transparency γ, and is lowest when the market is fully transparent: $p_s^o(1) = \beta_s(v_g - \omega_s)$, which is expression p_s^d in (2.3). Hence, market opacity increases the expected gain for the seller for any given price p_h^o offered by the hedger.

However, since in our model hedgers are unsophisticated but not naïve, we must consider that the offer price p_h^o is itself affected by the degree of market transparency. When the market is opaque ($\gamma < 1$), a Bayesian buyer will infer that there is a positive probability that the asset has been rejected by a speculator, that is, opacity creates asymmetric information between seller and investors. The seller who has been previously matched with a speculator knows that the match failed, but the hedger does not. Hence, there may be "informed" sellers, who went through a failed negotiation, or "uninformed" ones, who did not.

Following the literature on bargaining under asymmetric information (Ausubel et al. (2002), and the references therein), we assume that the hedger makes a take-it-or-leave-it bid to the seller. As shown by Samuelson (1984), for the trade to take place, a necessary and sufficient condition is that the buyer can make a profitable first-and-final offer. Then, altering the baseline case set out in the previous section, we modify the bargaining protocol when opacity generates information asymmetry between the seller and the hedger: we seek the price p_h^o that the hedger is willing to offer as a function of his beliefs about the asset's value, assuming he will not be able to infer it perfectly from the speculator's trading. As a result of the seller's informational advantage in the trading process, he extracts a rent from the hedger. When the hedger's likelihood μ of being the first to contact the seller is sufficiently low, this rent becomes so great that the hedger simply refrains from trading. This implies to the following proposition:

Proposition 17 *When the market is opaque, i.e. $\gamma < 1$, if the fraction of hedgers is high enough ($\mu \geq \underline{\mu}$), the price offered by the hedger is $p_h^o = \beta_s(v_g - \omega_s)(1 + a_h^*)/2$ and the seller accepts it. Otherwise ($\mu < \underline{\mu}$), the hedger does not trade.*

Intuitively, the fewer hedgers there are, the more leery they are of meeting the seller after a failed match and buying a low-value asset at a high price. At the limit, when the fraction of hedgers among all buyers μ drops below the threshold $\underline{\mu}$, this concern leads them to leave the market.
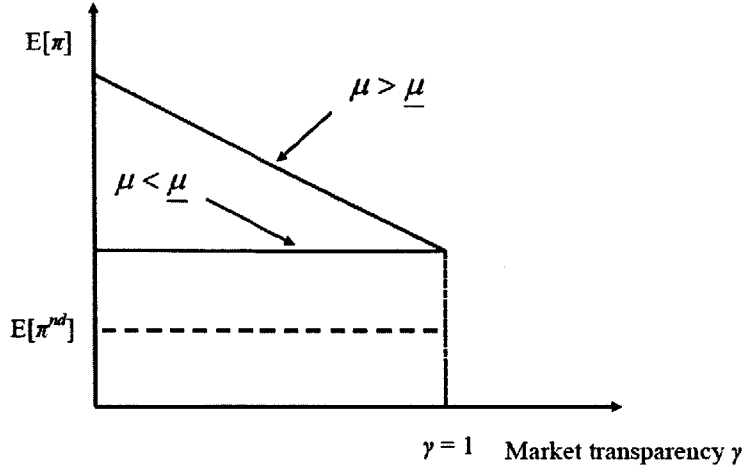
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Figure 2-2: Financial disclosure and market transparency: case (a)

Having characterized the hedger's trading strategy, we can calculate the seller's expected profit under disclosure $(d = 1)$ when the market is less than fully transparent $(\gamma < 1)$. Since the seller places no value on the asset, his profit coincides with the selling price. If $\mu \geq \underline{\mu}$, so that the hedger is present in the market, he sells to the speculator at the price $p_s^o(\gamma)$ in (2.11) with probability $\frac{1-\mu}{2}$ (since the speculator buys only if the asset value is high) and to the hedger at the price $p_h^o = \beta_s (1 + a_h^*) (v_g - \omega_s) / 2$; if instead $\mu < \underline{\mu}$, he can only sell to the speculator in the good state at price $\beta_s (v_g - \omega_s)$. Therefore the seller's profit under disclosure, when the market is not fully transparent, is:

$$\mathbb{E}(\pi^{o,d}) = \begin{cases} \frac{1-\mu}{2} p_s^o(\gamma) + \frac{\mu(1+a_h^*)}{2} \beta_s (v_g - \omega_s) & \text{if } \mu \geq \underline{\mu}, \\ \frac{1}{2} \beta_s (v_g - \omega_s) & \text{if } \mu < \underline{\mu}. \end{cases}$$

Recalling that by expression (2.11) the speculator's bid price $p_s^o(\gamma)$ is linearly decreasing in the degree of market transparency, when the hedger trades $(\mu \geq \underline{\mu})$ the seller's profit is also decreasing in γ. When the hedger does not trade $(\mu < \underline{\mu})$, the seller's profit does not depend on market transparency, but coincides with his lowest profit when the hedger is active.

The expected profits under disclosure for these two cases are plotted as a function of market transparency γ by the two solid lines in Figures 2 and 3. Notice that in both cases when the market achieves full transparency $(\gamma = 1)$, the seller's expected profit is the one he would
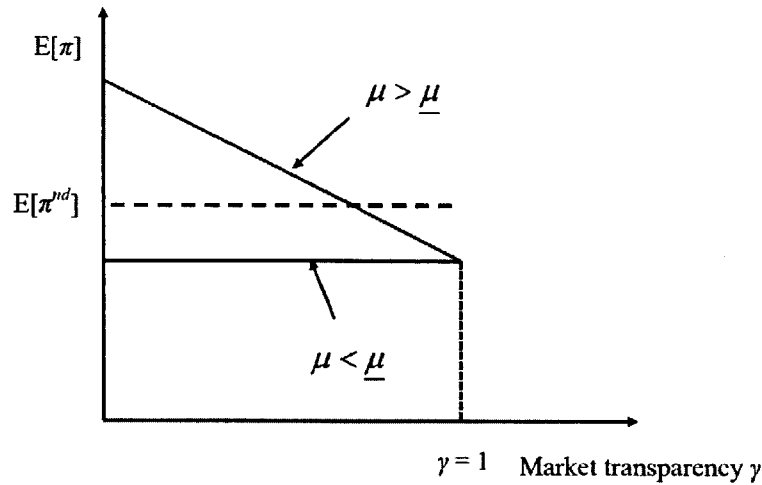
Figure 2-3: Financial disclosure and market transparency: case (b)

achieve if the hedger could capture the entire trading surplus by making a take-it-or-leave-it bid ($\beta_h = 0$ in Proposition 1). The negative relationship between average asset price and transparency for $\gamma \in [0,1)$ highlights that in our setting market transparency exacerbates the externality between hedger and speculator, which damages the seller.

We are now in a position to investigate whether the issuer opts for disclosure, and how this decision is affected by market transparency. First, notice that the expected profit with no disclosure $E(\pi^{nd})$ is not affected by market transparency, since the speculator refrains from trading and the expected profit is accordingly given by expression (2.6). This level of expected profit is shown as the dashed line in Figures 2 and 3. The figures illustrate two different cases. Figure 2 shows the case in which the expected profit under disclosure $E(\pi^{o,d})$ exceeds that under no disclosure $E(\pi^{nd})$ for any degree of market transparency: in this case, the issuer will always opt for disclosure ($d = 1$). Figure 3 shows the case in which if transparency γ is low and $\mu \geq \underline{\mu}$, the issuer prefers to disclose, but if transparency is high the issuer prefers not to disclose.

The following proposition summarizes the effects of market transparency on the issuer's incentive to disclose information:

Proposition 18 (Financial disclosure and market transparency) *(i) When the fraction of hedgers is sufficiently high ($\mu > \underline{\mu}$), the issuer's net benefit from disclosure is decreasing in*

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the degree of market transparency γ. (ii) Otherwise ($\mu < \underline{\mu}$), the issuer benefits more from disclosure when the market is fully transparent ($\gamma = 1$) than when it is not ($\gamma < 1$).

Proposition 18 shows that the issuer considers financial disclosure and market transparency as substitutes: he will always disclose more information in more opaque than in a more transparent market.

Our results differ considerably from the mainstream literature on market transparency (Glosten and Milgrom (1985), Kyle (1985), Pagano and Roell (1996), Chowhdry and Nanda (1991), Madhavan (1995) and Madhavan (1996) among others), which finds that opacity redistributes wealth from uninformed to informed investors. In our setting, instead, opacity damages both speculators and hedgers to the benefit of seller.[15] Speculators cannot fully exploit their superior processing ability, while the hedgers lose the chance to observe past order flow to update their beliefs about the asset's value.

Another difference from the prevalent literature is that our speculators would like to give their trading strategy maximum visibility, as by placing orders in non-anonymous fashion. This implication runs contrary to the traditional market microstructure view, that informed investors should prefer anonymity to avoid dissipating their informational advantage. Our result is consistent with the evidence in Reiss and Werner (2005), who examine how trader anonymity affects London dealers' decisions about where to place interdealer trades: surprisingly, informed interdealer trades tend to migrate to the direct and non-anonymous public market. Moreover, the experimental evidence in Bloomfield and O'Hara (1999) that trade transparency raises the informational efficiency of prices accords with our model's prediction that a more transparent market (higher γ) increases hedgers' ability to infer the asset value. Finally, Foucault et al. (2007) find that in the Euronext market uninformed traders are more aggressive when using anonymous trading systems, which parallels our result that hedgers are willing to offer a higher price when $\gamma = 0$.

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[15]Note that this result also differs from those of the existing models of the primary market, where opacity damages the seller (see for example Rock (1986))

2.6 Regulation

So far we have analyzed the issuer's incentives to disclose information, but not whether it is in line with social welfare. The recent financial crisis has highlighted the drawbacks of opacity, in both of our acceptations. For instance, the mispricing of asset-backed securities and the eventual freezing of that market were due chiefly to insufficient disclosure of risk characteristics as well as to the opacity of the markets in which they were traded. This has led some observers to advocate stricter disclosure requirements for issuers and greater transparency of markets; alternatively, others have proposed limiting access to these complex securities to the most sophisticated investors.

Our model can be used to analyze these policy options: the policy maker could (i) choose the degree of market transparency (set γ), (ii) make disclosure compulsory (set $d = 1$) and (iii) restrict market participation (for instance, ban hedgers from trading, setting $\mu = 0$).

2.6.1 Market transparency

There are several reasons why regulators might want to increase market transparency – to monitor the risk exposure of financial institutions, say, or to enable investors to gauge counterparty risk. Nevertheless, our analysis points to a surprising effect of greater transparency: it might reduce the issuer's incentive to divulge information. This effect stems from the endogeneity of the decision and the way in which it depends on market transparency γ.

As Figure 3 shows, the issuer's incentive to disclose the signal σ is decreasing in transparency γ. Hence, if the regulator increases γ beyond the intersection of the dashed line with the decreasing solid line, the seller will decide to conceal the signal σ, making the policy ineffective. In this case, in fact, speculators will abstain from trading, and the heightened transparency will actually reduce the information contained in the price. This will affect the hedgers' trading decision adversely, as they will have no information on which to base their decisions.

This result, which follows from Proposition 18, is summarized in the following corollary:

Corollary 19 *Increasing the degree of market transparency γ may ultimately reduce the information available to investors.*

This implication constitutes a warning to regulators that imposing transparency may back-

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fire, as a consequence of the potential response of market participants. Specifically, issuers' reaction might not only attenuate the effect of the policy, but actually result in a counterproductive diminution in the total amount of information available to investors, by reducing disclosure. This suggests that making the disclosure compulsory may be a better policy than regulating the degree of market transparency. The next section investigates when mandatory disclosure is socially efficient.

2.6.2 Mandating disclosure

In this section we analyze the conditions under which the regulator should make disclosure compulsory. We assume the regulator wishes to maximize the sum of market participants' surplus from trading, defined as the difference between the final value of the asset and the reservation value placed on it by the relevant buyer.

We compute the expected gains from trade when information is disclosed and when it is not. The expected social surplus when no information is disclosed is simply

$$\mathbb{E}\left[S^{nd}\right] = v^e - \omega_h,$$

while under disclosure it is

$$\mathbb{E}\left[S^d\right] = \mu\mathbb{E}\left[S_h^d\right] + (1 - \mu)\mathbb{E}\left[S_s^d\right], \tag{2.12}$$

that is, the expected value generated by a transaction with each type of investor.

The expected gain from a trade between the seller and a hedger is

$$\mathbb{E}\left[S_h^d\right] = \left[\frac{1 + a_h^*}{4}\left(v_g - \omega_h\right) + \frac{1 - a_h^*}{4}\left(v_b - \omega_h\right) + \frac{1 - a_h^*}{4}\left(v_g - \omega_s\right)\right] - \frac{\theta a_h^{*2}}{2}. \tag{2.13}$$

The first term is the surplus if the asset value is v_g and the realized signal is v_g, which occurs with probability $\frac{1+a}{4}$: the hedger buys the asset and the realized surplus is positive. The second term refers to the case in which the value is v_b but the hedger is willing to buy because the realized signal is v_g, which occurs with probability $\frac{1-a}{4}$: in this case the realized surplus is negative. The third term captures the case in which the hedger refrains from buying the asset

even though it was worth doing so, so that the asset is bought by the speculator. Finally, the last term is the information-processing cost borne by the hedger.

The expected gain from trade between the seller and a speculator instead is

$$\mathbb{E}\left[S_s^d\right] = \frac{v_g - \omega_s}{2}, \tag{2.14}$$

because the speculator only buys when the asset has high value, which occurs with probability $\frac{1}{2}$.

Recall that the main cost of disclosure for the issuer is the fall in price due to the information externality among investors, so that he is more willing to disclose when the seller's probability μ of being immediately matched with a hedger is high. For the regulator, instead, the main cost of disclosure consists in hedgers' information-processing costs, so the regulator is more willing to force disclosure when hedgers are less likely to buy, i.e. μ is lower. Hence:

Proposition 20 (Optimal disclosure policy) *Both under- and over-provision of information can occur in equilibrium. The regulator's net benefit from disclosure is decreasing in the hedgers' financial illiteracy θ, in the asset expected value v^e, and in the fraction μ of hedgers, and is increasing in the asset volatility $v_g - v_b$.*

The regulator's objective function differs from the seller's expected profits as computed earlier in three ways. First, the planner ignores the distributional issues driven by the bargaining protocol, so bargaining power does not affect the expected social gains. Second, the planner considers that disclosing information means the hedgers must investigate it, which is costly. Third, the regulator does not directly consider the externality generated by the speculators' superior processing ability and its effect on the seller's profit. This affects the social surplus only when it would be efficient for the seller to trade with the hedger, because of the latter's lower reservation value ω_h, and instead the asset is sold to a speculator. These differences generate the discrepancy between the privately and the socially optimal disclosure policy.

The fact that the over- or under-provision of information depends on information-processing costs and the seller's bargaining power is explained as follows. First, the social planner considers the total gains from trade, not the fraction accruing to issuers: on this account, the regulators' interest in disclosure is greater than the issuer's. At the same time, the issuer does

not directly internalize the cost of processing information, which is instead taken into account by the regulator. Interestingly, there is a region in which the seller has a greater incentive than the regulator for disclosure. This happens when enough hedgers participate in the market (high μ), where the issuer will disclose the signal σ even if it would be socially efficient to withhold it. This is even more likely if a high level of financial literacy is required (high θ), so that disclosure would imply high information-processing costs for hedgers.

Conversely, in a market with a large share of speculators (low μ), the issuer will fear their superior processing ability, and so will not disclose even when it would be socially efficient. This is likely in the markets for complex assets, such as asset-backed securities, where considerable sophistication is required to understand the structure of the asset and its pricing implications, so that speculators are more likely to participate. Hence, in such markets mandating information disclosure by sellers is warranted. This probably does not apply to markets for treasuries and simple corporate bonds, where the speculators' information-processing ability gives them a smaller advantage.

2.6.3 Licensing access

In practice, policy makers also have other instruments to regulate financial markets so as to maximize the expected gains from trade. Stephen Cecchetti, head of the BIS monetary and economic department, for example, has suggested that to safeguard investors "The solution is some form of product registration that would constrain the use of instruments according to their degree of safety." The safest securities would be available to everyone, much like non-prescription medicines. Next would be financial instruments available only to those with a licence, like prescription drugs. Finally would come securities available "only in limited amounts to qualified professionals and institutions, like drugs in experimental trials". Securities "at the lowest level of safety" would be illegal.[16] A step in this direction has already been taken in the context of securitization instruments: issuers of Rule 144a instruments, which require a high degree of sophistication, can place them with dealers who can resell them only to Qualified Institutional Buyers, while registered instruments can be traded by both retail and institutional

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[16]*Financial Times*, June 16 2010 available at http://cachef.ft.com/cms/s/0/a55d979e-797b-11df-b063-00144feabdc0.html#axzz1JDvAWQa2.

investors.

Since speculators, when they get the signal σ, forecast the asset's value perfectly and incur no processing costs, it might be optimal to limit market participation to them, thereby inducing the seller to disclose information. Limiting access to speculators only is a socially efficient policy when the expected surplus generated by trading with them (2.14) exceeds the expected gain (2.12) generated by the participation of all types of investors. The relevant condition is

$$\frac{v_g - \omega_s}{2} > \mu \left[\frac{1 + a_h^*}{4} v_g + \frac{1 - a_h^*}{4} v_b - \omega_h + \frac{1 - a_h^*}{4} (v_g - \omega_s) - \frac{\theta a_h^{*2}}{2} \right] + (1 - \mu) \frac{v_g - \omega_s}{2}, \quad (2.15)$$

which leads to the following proposition:

Proposition 21 (Ban hedgers from trading) *Making market access exclusive to speculators is welfare-improving when financial illiteracy θ is high and the expected value v^e of the asset is low. For the issuer this policy is never optimal.*

In this case too, therefore, the issuer's and the regulator's incentives are not aligned: in fact, issuers are always hurt by a policy that excludes hedgers, even when they deal with complex assets and unsophisticated investors. In contrast, Proposition 21 indicates that in these circumstances it may be socially efficient to limit access to speculators alone, because this saves hedgers from the high processing costs incurred when information is difficult to digest.

However, restricting access is not always optimal. In particular, it is inefficient when the expected asset value v^e is high: in this case the expected gains from trade are greater when all investors participate and it is less likely that hedgers will buy the asset when it is not worth it. Finally, volatility $v_g - v_b$ has ambiguous effects on the regulator's incentive to exclude hedgers: on the one hand, it raises the costs associated with their buying a low-value asset, and hence the regulator's interest in keeping them out of the market; on the other hand, it induces hedgers to step up their attention level, making the regulator more inclined to let them in.

2.7 Conclusion

We propose a model of financial disclosure in which some investors (whom we call "hedgers") are bad at information processing, while others ("speculators") trade purely to exploit their

superior information processing ability. We make three main contributions.

First, we show that enhancing information disclosure may not benefit hedgers, but can actually augment the informational advantage of the speculators. A key point is that disclosing information about fundamentals induces an externality: since speculators are known to understand the pricing implications, hedgers will imitate their decision to abstain from trading, driving the price of the asset below its no-disclosure level.

Second, we investigate how this result is affected by the opacity of the market, as measured by the probability of investors observing previous orders placed before theirs. This has two effects. On the one hand, in a more opaque market hedgers cannot count on information extracted from the speculators' trading strategy, which attenuates the pricing externality and favors the seller, so that opacity increases the seller's incentive for disclosure. On the other hand, opacity creates an information asymmetry between seller and hedgers, which in extreme cases might even lead the latter to leave the market entirely.

Third, in general the issuer's incentives to disclose are not aligned with social welfare considerations, thus warranting regulatory intervention. For instance, disclosure must be made compulsory when speculators constitute a large fraction of market participants, a situation in which the issuer would otherwise withhold information to prevent speculators from exploiting their superior processing ability. Similarly, excluding hedgers from the market may be optimal when their processing costs are high – a policy that always damages sellers.

2.8 Appendix

2.8.1 Proofs of Propositions

Proof of Proposition 1

We first solve the bargaining stage of the game taking the seller's outside options as given. Then we compute these outside options to get the equilibrium prices. Let us restate the Nash bargaining problem of the two investors:

$$\max_{p_i} \beta_i \log\left(p_i - \bar{\omega}_i\right) + \left(1 - \beta_i\right) \log\left(\hat{v} - p_i - \omega_i\right), \text{ for } i \in \{h, s\}.$$

Solving for p_i, we obtain

$$p_i = \beta_i \left(\hat{v} - \omega_i - \bar{\omega}_i\right) + \bar{\omega}_i, \tag{2.16}$$

where $\hat{v}$ is the investor's estimate of the value of the asset and $\bar{\omega}_i$ is the seller's outside option after meeting investor i. Therefore the price to the seller includes his outside option and a fraction β_i of the total surplus. The investor's expected payoff is

$$
\begin{aligned}
u_i = \hat{v} - p_i - \omega_i &= \left(\hat{v} - \omega_i - \bar{\omega}_i\right)\left(1 - \beta_i\right) \\
&= \mathbb{E}\left[\left(v - \omega_i - \bar{\omega}_i\right)\left(1 - \beta_i\right) |\Omega_i\right].
\end{aligned}
$$

Next, we investigate the possible strategies of the hedger in a second match following a first match between seller and speculator that results in no trade. We conjecture that in equilibrium $a_s^* = 1$ and $a_h^* < 1$. Since the outcome of the seller's negotiation with the speculator is observable, if the hedger sees that no trade occurred he infers that the asset is of low quality, so that the seller's outside option after being matched with the speculator is zero: $\bar{\omega}_s = 0$. Substituting this into expression (2.16) yields the price paid by the speculator:

$$p_s = \beta_s \left(v_g - \omega_s\right).$$

Now suppose the seller is initially matched with a hedger who has observed a positive signal

v_g. The hedger's belief about the asset being of high value is

$$\phi\left(v_g | v_g\right) = \frac{\frac{1+a_h}{2}\frac{1}{2}}{\frac{1}{2}} = \frac{1+a_h}{2}.$$

If the negotiation fails and no trade occurs, the seller keeps searching until he meets the speculator. If he trades with the speculator, he gets the price p_s, so that his outside option if initially matched with the hedger is

$$\bar{\omega}_h = \begin{cases} \beta_s \frac{1+a_h}{2}\left(v_g - \omega_s\right) & \text{if } \sigma = v_g, \\ \beta_s \frac{1-a_h}{2}\left(v_g - \omega_s\right) & \text{if } \sigma = v_b. \end{cases} \tag{2.17}$$

Substituting (2.17) into expression (2.16) yields the equilibrium price paid by the hedger:

$$p_h^d = \beta_h\left(\hat{v} - \omega_h\right) + \left(1 - \beta_h\right)\beta_s \frac{1+a}{2}\left(v_g - \omega_s\right),$$

as stated in the proposition.

Proof of Proposition 2

Given the bargaining protocol, the hedger captures only a fraction $1 - \beta_h$ of the trading surplus, so his expected payoff is

$$
\begin{aligned}
u\left(a_h\right) &= \left(1 - \beta_h\right)\left(\hat{v}\left(a_h, v_g\right) - \omega_h - \bar{\omega}_h\right) \\
&= \left(1 - \beta_h\right)\left(\frac{1+a_h}{2}v_g + \frac{1-a_h}{2}v_b - \omega_h - \bar{\omega}_h\right) \\
&= \left(1 - \beta_h\right)\left[v^e - \omega_h - \frac{1+a_h}{2}\left(v_g - \omega_s\right)\beta_s + \frac{a_h}{2}\left(v_g - v_b\right)\right],
\end{aligned}
$$

where expression (2.17) is used in the last step.

Then, the optimal attention allocation solves the following maximization problem:

$$\max_{a_h \in [0,1]} \frac{1}{2}u\left(a_h\right) - \frac{1}{2}\theta a_h^2.$$

The solution is

$$a_h^* = \frac{\left[\left(v_g - v_b\right) - \beta_s\left(v_g - \omega_s\right)\right]\left(1 - \beta_h\right)}{4\theta} = \left(v_g - v_b\right)\frac{\left(1 - \beta_s\right)\left(1 - \beta_h\right)}{4\theta},$$

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where we have used the parameter restriction $\omega_s = v^e = (v_g + v_b)/2$.

Clearly $a_h^* > 0$. The condition for a_h^* to be interior, $a_h^* \leq 1$, is given by

$$\theta > (v_g - v_b)(1 - \beta_s)(1 - \beta_h)/4,$$

which is the parameter restriction in Assumption 2. The comparative statics results set out in the proposition clearly follow from this expression for a_h^*.

The expected payoff for the speculator is similar to that of the hedger:

$$
\begin{aligned}
u(a_s) &= (1 - \beta_s)(\hat{v}(a_s, v_g) - \omega_s - \bar{\omega}_s) \\
&= (1 - \beta_h)\left(v^e - \omega_s + \frac{a_s}{2}(v_g - v_b)\right),
\end{aligned}
$$

where in the second step we have used $\bar{\omega}_s = 0$. Recall that the speculator incurs no information-processing cost; so he simply maximizes $\frac{1}{2}u(a_s)$, which is increasing in a_s. Hence his optimal attention is the corner solution $a_s^* = 1$.

We can show that if asset volatility is sufficiently high it is optimal for the hedger to buy only after a positive signal v_g is revealed. The hedger trades only when good news is released if the following condition holds:

$$\frac{1 - \beta_h}{2}\left[v^e - \omega_h - \frac{1 + a}{2}\frac{v_g - v_b}{2}\beta_s + \frac{a}{2}(v_g - v_b)\right] - \theta\frac{a^2}{2} > (1 - \beta_h)(v^e - \omega_h), \qquad (2.18)$$

where the left-hand side is the expected payoff conditional on buying after good news and the right-hand side is the expected payoff of buying regardless of the type of news. In the latter case it is optimal for the hedger not to pay any attention, i.e. make any effort to understand the signal: $a_h^* = 0$. Condition (2.18) can be re-written as follows:

$$\frac{v_g - v_b}{v^e - \omega_h}\left[\frac{3}{4}a_h^*\left(1 - \frac{\beta_s}{2}\right) - \frac{\beta_s}{2}\right] > 1.$$

which shows that for sufficiently high values of asset volatility $v_g - v_b$, it becomes optimal for the hedger to buy only upon seeing a positive signal. Notice that when this condition holds, the hedger will want to buy the asset, since he expects a positive payoff $u(a_h^*)$, the left-hand

expression in inequality (2.18) being positive (since $v^e - \omega_h > 0$).

Proof of Proposition 3

To prove this proposition, we compute total expected profits under disclosure ($d = 1$):

$$
\begin{aligned}
\mathbb{E}\left[\pi^d\right] &= \mu \frac{1+a}{4}\left(p_h^d - p_s\right) + \frac{1}{2}p_s &(2.19)\\
&= \mu \frac{1+a}{4}\left[\beta_h\left(\hat{v} - \omega_h\right) + (1 - \beta_h)\frac{1+a}{2}p_s - p_s\right] + \frac{1}{2}p_s \\
&= \mu \frac{1+a}{4}\left[\beta_h\left(v^e - \omega_h\right) + \beta_h \frac{v_g - v_b}{2} + (1 - \beta_h)\frac{1+a}{2}p_s - p_s\right] + \frac{1}{2}p_s \\
&= \mu \frac{1+a}{4}\left[\beta_h\left(v^e - \omega_h\right) + \left(\beta_h + (1 - \beta_h)\frac{1+a}{2}\beta_s - \beta_s\right)\frac{v_g - v_b}{2}\right] + \frac{1}{2}p_s > 0,
\end{aligned}
$$

where in the first two steps we have substituted the expressions for the prices and imposed the restriction $\omega_s = v^e$ on the speculator's outside option, and in the third we have used the fact that $p_s = \beta_s \left(v_g - v_b\right)/2$. The final inequality follows from the assumption that $\beta_h \geq \beta_s$. The issuer's choice on disclosure depends on the expected profit under disclosure (2.19) and under no disclosure (2.6). In this comparison, the only terms involving the parameters $\{\mu, v_g - v_b, \theta\}$ mentioned in Proposition 3 appear in expression (2.19). The issuer's expected benefit from disclosure is clearly increasing in μ, because $p_h^d > p_s$, as shown. Volatility of value has two effects: first, a direct positive effect via prices, as shown by the terms inside the parenthesis in (2.19) (again recalling that $\beta_h \geq \beta_s$); and second, an indirect positive effect via the attention allocation a_h^*, recalling that $\frac{\partial a_h^*}{\partial (v_g - v_b)} > 0$ from Proposition 2. Finally, the financial illiteracy parameter θ affects the issuer's expected profit only through its effect on the optimal choice of attention a_h^*: since $\frac{\partial a_h^*}{\partial \theta} < 0$ by Proposition 2, an increase in θ reduces the issuer's benefit from disclosing.

Proof of Proposition 4

To solve for the hedger's equilibrium price, notice that a buyer must consider whether his bid is such that the seller will accept it or not. A seller who has not been previously matched with a speculator will require at least a price that compensates him for his outside option, which is to sell to a speculator: hence $p_h^o \geq \beta_s \left(1 + a_h^o\right)\left(v_g - \omega_s\right)/2$, since the speculator would buy only if the value of the asset is high, which occurs with probability $\left(1 + a_h^o\right)/2$. Instead, a seller who

knows that his previous match failed will accept any offer from the subsequent buyer. Hence, the hedger's belief about being the first to be matched with the seller is given by

$$\widehat{\mu} = \begin{cases} \frac{\mu}{\mu + (1-\mu)/2} & \text{if } p_h^o \geq \beta_s \left(1 + a_h^o\right) \left(v_g - \omega_s\right)/2, \\ 0 & \text{if } p_h^o < \beta_s \left(1 + a_h^o\right) \left(v_g - \omega_s\right)/2, \end{cases} \qquad (2.20)$$

where it is easy to see that the belief $\widehat{\mu}$ is increasing in the hedger's probability μ of being the first to contact the seller, and therefore in the fraction of hedgers in the market.

Hence, the hedger faces a new adverse selection problem: if his bid price is below $\beta_s \left(v_g - \omega_s\right) \left(1 + a_h^o\right)/2$, first-time sellers will reject the offer, while previously unsuccessful sellers will accept it, so he is certain to acquire a low-quality asset. However, a bid price above $\beta_s \left(v_g - \omega_s\right) \left(1 + a_h^o\right)/2$ would be wasteful. Hence, the hedger will offer $p_h^o = \beta_s \left(v_g - \omega_s\right) \left(1 + a_h^o\right)/2$. This price makes first-time sellers just break even, but leaves a rent to previously unsuccessful sellers, who get a positive price for a worthless asset.

The fact that the hedger pays an adverse-selection rent raises the issue of whether he will want to participate at all. Here, it is convenient to define the hedger's expected surplus from buying the asset:

$$\Gamma\left(\mu\right) \equiv \widehat{\mu}\widehat{v}(a_h, v_g) + \left(1 - \widehat{\mu}\right) v_b - \omega_h - p_h^o,$$

where the first term refers to the expected value when the hedger is the first to be matched with the seller, and the second to the value when he is the second. Since $\widehat{v} > v_b$, the hedger's expected surplus Γ is increasing in his probability μ of being the first match. Thus his surplus is zero if μ is low enough to make the belief $\widehat{\mu}$ sufficiently pessimistic: denoting by $\underline{\mu}$ the threshold such that $\Gamma\left(\underline{\mu}\right) = 0$, for any $\mu < \underline{\mu}$ the hedger will not want to participate in the market. Such a cutoff $\underline{\mu}$ exists and is unique because $\Gamma\left(0\right) = v_b - \omega_h - p_h^o < 0$, and when $\mu = 1$ the expected payoff for the hedger is $\Gamma\left(1\right) = \widehat{v} - \omega_h - p_h^o$, which is positive as long as there are gains from trade, i.e. whenever the hedger observes a good signal. Then the strict monotonicity of $\Gamma\left(\mu\right)$ ensures that there exists a unique cutoff $\underline{\mu}$, defined by $\Gamma\left(\underline{\mu}\right) = 0$, such that trade occurs at a positive price whenever $\mu > \underline{\mu}$.

Following the proof of Proposition 2 it is straightforward to show that when $\gamma < 1$ the

hedger's optimal attention is given by

$$a_h^o = (v_g - v_b) \frac{(1 - \beta_s)}{4\theta} > a_h^* = (v_g - v_b) \frac{(1 - \beta_s)(1 - \beta_h)}{4\theta}$$

This concludes the proof.

Proof of Proposition 5

Point (i) of the Proposition follows from the fact that when $\mu > \underline{\mu}$ the issuer's expected profit is

$$\mu \mathbb{E}[\pi_h^o] + (1 - \mu) \mathbb{E}[\pi_s^o] = \mu p_h^o + (1 - \mu) p_s$$
$$= \mu \frac{\beta_s (1 + a_h^*)(v_g - \omega_s)}{2} + (1 - \mu) \left[\frac{\beta_s (v_g - \omega_s)}{2} + (1 - \beta_s)(1 - \gamma) \frac{1 + a}{4} p_h^o \right],$$

where in the second step the hedger's equilibrium price p_h^o has been substituted in from Proposition 4. As is evident from this expression, the issuer's expected profit under disclosure is decreasing in the degree of market transparency γ. Since under no disclosure this profit is not affected by γ, point (i) of the Proposition follows immediately.

We now demonstrate point (ii): when $\mu < \underline{\mu}$, i.e. when hedgers opt out of the market, the issuer prefers to disclose if the market is fully transparent. To show this, simply compare the issuer's expected profit under disclosure in a fully transparent market ($\gamma = 1$) and in an opaque market ($\gamma < 1$):

$$\mu \mathbb{E}[\pi_h^t] + (1 - \mu) \mathbb{E}[\pi_s^t] = \mu \frac{1 + a}{4} \left(p_h^d - p_s \right) + \frac{1}{2} p_s$$
$$> \frac{1}{2} p_s = \mathbb{E}[\pi_s^o],$$

where the first line represents the expected payoff with disclosure the signal in a transparent market, with $p_h^d > p_s$ as shown in Proposition 3, and the second the expected profit with disclosure in an opaque market in which hedgers do not participate. This proves the second point of the proposition.

Proof of Proposition 6

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The regulator's net benefit is the difference between the expected social surplus with and without disclosure, Δ:

$$\Delta \equiv \mathbb{E}\left[S^d\right] - \mathbb{E}\left[S^{nd}\right] = \mu\left[\frac{1+a}{4}\left(v_g - \omega_h\right) + \frac{1-a}{4}\left(v_b - \omega_h\right) + \frac{1-a}{4}\left(v_g - \omega_s\right) - \theta\frac{a^2}{2}\right]$$

$$+ \left(1 - \mu\right)\left(\frac{v_g - \omega_s}{2}\right) - v^e + \omega_h$$

$$= \mu\left[\frac{v_g + v_b}{4} + a\frac{v_g - v_b}{4} - \omega_h + \frac{1-a}{4}\frac{\left(v_g - v_b\right)}{2} - \theta\frac{a^2}{2}\right] + \left(1 - \mu\right)\left(\frac{v_g - \omega_s}{2}\right) - v^e + \omega_h$$

$$= \mu\left[\frac{v_g - v_b}{8} + \frac{a}{8}\left(v_g - v_b\right) - \theta\frac{a^2}{2}\right] - v^e\left(1 - \frac{\mu}{2}\right) + \left(1 - \mu\right)\omega_h + \left(1 - \mu\right)\left(\frac{v_g - \omega_s}{2}\right).$$

It is easy to see that $\frac{\partial\Delta}{\partial\omega_h} > 0$ and $\frac{\partial\Delta}{\partial v^e} < 0$. Moreover, one can show that $\frac{\partial\Delta}{\partial\theta} < 0$:

$$\frac{\partial\Delta}{\partial\theta} = \frac{\left(v_g - v_b\right)}{8}\frac{da}{d\theta} - \frac{a^2}{2} - \theta a\frac{da}{d\theta},$$

where

$$\frac{da}{d\theta} = -\frac{\left(1 - \beta_h\right)\left(1 - \beta_s/2\right)\left(v_g - v_b\right)}{4\theta^2},$$

so that substituting this expression into the previous one and re-arranging yields $\frac{\partial\Delta}{\partial\theta} < 0$.

The result that $\frac{\partial\Delta}{\partial(v_g - v_b)} > 0$ is shown as follows:

$$\frac{\partial\Delta}{\partial(v_g - v_b)} = \mu\left[\frac{a}{8} + \frac{v_g - v_b}{8}\frac{da}{d(v_g - v_b)} + \frac{1}{8} - \theta a\frac{da}{d(v_g - v_b)}\right] + \frac{\left(1 - \mu\right)}{4}$$

$$= \mu\left[\begin{array}{c}\frac{(1-\beta_h)(1-\beta_s/2)(v_g - v_b)}{32\theta} + \frac{v_g - v_b}{8}\frac{(1-\beta_h)(1-\beta_s/2)}{4\theta} \\ +\frac{1}{8} - \frac{(1-\beta_h)(1-\beta_s/2)(v_g - v_b)}{4}\frac{(1-\beta_h)(1-\beta_s/2)}{4\theta}\end{array}\right] + \frac{\left(1 - \mu\right)}{4}$$

$$= \mu\left[\frac{(1-\beta_h)(1-\beta_s/2)(v_g - v_b)}{16\theta} + \frac{1}{8} - \frac{(1-\beta_h)^2(1-\beta_s/2)^2(v_g - v_b)}{16\theta}\right] + \frac{\left(1 - \mu\right)}{4} > 0,$$

where the inequality follows from $\frac{(1-\beta_h)(1-\beta_s/2)(v_g - v_b)}{16\theta} > \frac{(1-\beta_h)^2(1-\beta_s/2)^2(v_g - v_b)}{16\theta}$ because $\beta_i \in (0, 1)$.

To show that there might be either under-provision and over-provision of information, we show that depending on parameter values there are cases in which the regulator would compel disclosure but the issuer would not want to disclose, and also the other way around. We denote by Δ the net benefits from disclosing for society (and thus for the regulator) and by

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$G = E(\pi^d) - E(\pi^{nd})$ the gain for the issuer. In the following table we show two possible cases: in the first, the regulator finds disclosure optimal and the seller does not, while in the second the issuer discloses the signal even though it is socially optimal to conceal it.

	v_g	v_b	ω_h	μ	θ	β_h	β_s	a_h^*	G	$\Delta\pi$
Case 1: Under-provision	10	-1	3	0.1	1	0.8	0.5	0.41	1.23	0.29
Case 2: Over-provision	10	-1	3	0.9	1	0.9	0.8	0.16	0.87	1.41

The first case shows that the issuer does not gain from disclosing the signal if he has low bargaining power vis-à-vis the speculator $\beta_s = 0.5$ and when μ is sufficiently small ($\mu = 0.1$). Intuitively, when the asset is likely to be sold to the speculator, the issuer refrains from disclosing the signal to avoid the implied underpricing. The second case shows that the regulator would prefer the signal not to be disclosed if the fraction of hedgers in the market is high ($\mu = 0.9$), while in this case the issuer has the incentive to disclose because he is able to capture most of the surplus generated by trade with either the hedger or the speculator ($\beta_h = 0.9$ and $\beta_s = 0.8$).

Proof of Proposition 7

That the issuer never wants to exclude hedgers from the market, it is demonstrated simply by the fact that his expected profit with full market participation is greater than under restricted participation:

$$\mu \frac{1+a}{4} \left(p_h^d - p_s \right) + \frac{1}{2} p_s > \frac{1}{2} p_s.$$

The regulator, however, will want to restrict market participation to the speculators when the resulting expected loss L is negative; that is, from condition (2.15)

$$\mathbb{L} \equiv \frac{v^e}{2} - \omega_h + \frac{a}{8} \left(v_g - v_b \right) - \frac{v_g - v_b}{8} - \theta \frac{a^2}{2} < 0. \tag{2.21}$$

By the same steps as in the proof of Proposition 6, it can be shown that $\frac{\partial \mathbb{L}}{\partial \theta} < 0$, implying that the regulator's interest in barring hedgers increases as the complexity θ of the asset increases. From expression (2.21), it is straightforward to show that a higher expected asset value v^e reduces the regulator's interest in excluding hedgers. The effect of asset volatility $v_g - v_b$ on

expression (2.21) is ambiguous.

2.8.2 Robustness to alternative bargaining protocols

In this section we discuss how different bargaining protocols would affect our results.

First, in the previous analysis the less informed agent – the hedger – has been assumed to always capture part of the trading surplus. In fact, if the seller were to appropriate all the surplus when trading with the hedger ($\beta_h = 1$), the latter would have no incentive to process information resulting in $a_h^* = 0$ (as can be seen from the expression for a_h^* in Proposition 2) and the hedger would end up always purchasing the asset (whose expected value exceeds his outside option: $v^e > \omega_h$). We rule out this uninteresting case by assuming that the hedger can capture a portion of the trading surplus.

Second, there are two additional possible cases to consider according to the information possessed by the seller. In the text we restrict attention to the case in which the dealer in charge of the sale of the asset has no information about its value. In this case, if the hedger can make a take-it-or-leave-it bid as assumed in Section 2.5, he will offer the expected value of the seller's outside option, which is the price the speculators are willing to offer when they trade. Then, the analysis closely follows that in Section 2.4, simply by setting $\beta_h = 0$.

If instead the seller is informed about the value of the asset v, then when he is matched with the hedger a classic adverse selection problem emerges, even if the market is fully transparent ($\gamma = 1$). If the seller can make offers to the buyer, a signaling game between the parties would lead to multiple equilibria depending on off-equilibrium beliefs. This complication can be avoided by assuming again that the less informed agent, the hedger, makes an ultimatum offer to the seller. Then, the analysis of Section 2.4 would closely resemble that developed in Section 2.5, because the hedger would offer $p_h = (v_g - \omega_s)\beta_s(1 + a_h)/2$ and would trade if and only if his expected profit is positive. In this case, the expected profit of the seller under disclosure would be $(v_g - \omega_s)\beta_s(1 + a_h)/2$, as both types of investors would offer the same price. The only difference from the analysis proposed in the text is that the optimal disclosure policy (characterized in Proposition 3) would not depend upon the fraction of hedgers μ that participate to this market.

Chapter 3

Reputation Traps, Tail Risk and the Business Cycle

3.1 Introduction

In 2008 the global asset management industry managed a total of $90 trillion, through pension funds, mutual funds and hedge funds. This squares with the substantial increase in the institutional ownership of corporate equity, from 7.2% in 1950 to 78% in 2007 (French (2008)). This sheer size and the ability to engage in sophisticated trading strategies through leverage, through the use of derivatives and by taking short positions makes institutional investors a key player in the financial markets. Moreover, their performance is constantly monitored by capital providers such as investors and lenders, which induces fund managers to be concerned about their perceived ability.

However, the effectiveness of market discipline in shaping institutional investors' conduct has been seriously challenged by the recent financial crisis. The cases of Bear Stearns High-Grade Structured Credit Fund, which misled investors into a sinking fund, or of the fund manager David Einhorn, whose short selling famously helped to bring down Lehman Brothers, are just few cases.[1] Furthermore, institutional investors might amplify aggregate shocks by taking ex-

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[1] "Two Bear Stearns executives shared their growing fears in a series of e-mail messages to each other about the perilous condition of the giant hedge funds they oversaw. "I'm fearful of these markets," one wrote. But three days later, the pair, Ralph R. Cioffi and Matthew M. Tannin, presented an upbeat picture to worried

cess risk (Huang et al. (2011)), riding bubbles (Brunnermeier and Nagel (2004)) or hoarding liquidity when it is most needed (Ben-David et al. (2007)). The collapse of financial markets' discipline as a key element of crises has been highlighted by the current Federal Reserve chairman, Ben Bernanke: "Market discipline has in some cases broken down." Is it possible that managers' concerns about gaining and maintaining good reputations are responsible for these distortions? How does market discipline interact with aggregate uncertainty to affect fund managers' strategies? In this paper, we show that market discipline might in fact generate perverse incentives and induce more risk-taking and less effort exertion by reputable fund managers, which has significant aggregate consequences.

I begin with a model of money management in which fund managers attract funds from investors and affect both the returns and the risk exposure of the fund. First, I focus on the managers' possibility to generate active returns at a disutility to illustrate how reputation concerns aimed at relaxing agency problems impact fund manager's incentives. In the model, there are "skilled" managers who have an advantage in generating returns, while some of them are "unskilled" and have to incur a cost to find the most profitable investment opportunities. A manager's reputation is defined as the investors' belief that the manager is "skilled". Manager's reputation changes over time as investors observe the funds' returns. Unskilled managers want to pool themselves with the skilled ones to attract more capital from investors in the future and earn higher commissions. The fear of losing reputation, therefore, leads unskilled managers to identify the investment strategies that will generate excess returns over the risk-free asset.

The first main result is the rich dynamics that the model is able to deliver. It is possible to identify three regions according to the level of the managers' reputation. First, there exists an exploitation region, in which good-reputation managers extract the rents associated with their "star status" by maximizing their myopic payoff. Second, there exists a reputation building region, i.e. managers with intermediate reputation aim to improve their reputations by delivering higher returns, but at a rate that is decreasing in their perceived reputation. Finally, managers

investors without disclosing that the two funds were plummeting in value and that Mr. Cioffi had already pulled some assets from one of them. A little more than a month later, the funds, filled with some of the most explosive and high-risk securities available, imploded, evaporating $1.6 billion of investor assets and setting off a financial chain reaction that has rattled global markets, caused more than $350 billion in write-downs, cost a number of executives their jobs and culminated in the demise of Bear Stearns itself." (*New York Times, June 20, 2008.* Available at http://www.nytimes.com/2008/06/20/business/20bear.html?_r=1&hp&oref=slogin)

with poor reputations can end up in a reputation trap, in which investors' confidence in their ability is so low that they are not willing to allocate any more capital to the managers, which, in turn, dampens the possibility of improving their reputation.

The second main contribution is that the way in which funds managers amplify fluctuations can be decomposed into two effects. First, there exists a composition effect. Managers are more likely to be caught in a reputation trap and it is more likely for an unskilled manager to be lucky and attract investors' support as market volatility increases. This means that the composition of the managers able to attract funds chages in a downturn. Moreover, in a more volatile economy it is harder for the manager to affect investors' beliefs, which squares with the evidence in Huang et al. (2011). This leads to the emergence of a strategic effect as well. Due to the effect working through the investors' learning, managers with a high reputation have a very high incentive to exploit their reputation, because they expect their actions not to influence the investors' decision. Then, downturns are also periods in which the agency costs increase due to the incentive of the high-reputation managers to behave myopically.

The existence of a reputation trap also affects the managers' risk-taking behavior. The manager is willing to increase the short-term returns by exposing the fund to tail-risk. This has two effects. First, this benefits the manager in the short run by increasing his performance fees. Second, it might induce returns-chasing investors to update their beliefs about the manager and allocate more capital to the fund. This means that as market volatility increases, like during periods of financial turmoil, institutional investors with low reputations are more prone to expose themselves to tail risk, which further amplifies the effects of a crisis.

Then, I extend the model to capture aggregate uncertainty about the state of the economy. In the model, it is possible to capture periods of crisis by assuming that returns will be lower and more volatile. I show this generates two types of new incentives for the managers. First, in expectation of a crisis, low-reputation managers rationally expect to enter a reputation trap and lose investors' capital independently by their current actions. This might capture the "flight to safety" of investors during periods of high uncertainty. Then, managers with low reputation can try to "gamble to resurrect" by exposing their fund to excessive risk. In the event of a positive shock, they will increase their reputation and improve market confidence about their abilities. Second, managers with good reputations who expect a crisis in the future might try to preserve

their status by hoarding more liquidity by investing in risk-free assets. Then, exactly when investors could make good use of the managers' superior skills, their market discipline induces them to exit from the market or exacerbate the shocks by taking too much risk. Moreover, the managers with higher reputations attract more funds from investors, which means that more capital is detracted from more profitable use.

One might think that good-reputation managers would leverage their reputations to exploit the most profitable opportunities made available by the depressed market conditions. However, we show this is not the case, because star performers value their reputation so highly that they prefer to preserve it by "playing it safe" during times of market turmoil. The poor-reputation managers, instead, are more willing to make extreme bets both before and during the crisis. Since they expect to lose investors' funds during a crisis no matter what actions they take, fund managers with intermediate and low reputations are in equilibrium more willing to jeopardize their funds.

The model delivers several novel empirical implications regarding the managers' behavior over the business cycle. First, high volatile periods are amplified by the intermediaries who are able to attract funds even when unskilled, which amplifies the investors' effective risk profiles. Second, the performance history of these intermediaries should significantly affect their portfolio allocation. Third, the incentives to employ the exposure to tail risk change over time, i.e. we should observe the intermediaries' portfolio become more and more negatively skewed as they forecast market turmoil. Moreover, these implications also contribute to the policy makers' attempt to regulate the financial intermediation industry. In fact, the financial crisis has illustrated the importance of the role played by institutional investors, but up to now, the focus of the policies under discussion has been on their explicit incentives, mainly their bonus and stock options, and how these might affect their risk-taking behavior. Here, I show that a neglected factor affecting the managers' behavior is their implicit incentives. This might actually make their action procyclical.

Relation with the literature. This paper contributes to the broad literature on career concerns in financial markets, which has shown that institutional investors who care about their reputations herd (Scharfstein and Stein (1990), Zwiebel (1995) and Ottaviani and Sorensen (2006)), prevent information aggregation (Dasgupta and Prat (2006) and Dasgupta and Prat

(2008)), have limited ability to pursue arbitrage opportunities (Shleifer and Vishny (1997)) and amplify price volatility in financial markets (Guerrieri and Kondor (2009)). This paper's focus is on the impact of excessive risk taking and inefficient liquidity hoarding by institutional investors in amplifying aggregate fluctuations in financial markets. In particular, we show that reputation concerns, driven by investors' learning about manager's skill, might generate patterns of behavior very differently according to their reputation and the state of the economy.

Other studies that model learning about managerial skill with a focus that differs from ours include Lynch and Musto (2003), Berk and Green (2004), Huang et al. (2011), Dangl et al. (2008) and Malliaris and Yan (2010). Lynch and Musto (2003) shows that fund managers change strategies following poor performance, and bad performers who change strategy have flow and future performance less sensitive to current performance than those who do not. Berk and Green (2004), instead, show that performance might not be persistent even when managers have heterogeneous skill, if the investors delegate their funds to best-performing funds and the latter have lower returns in managing bigger funds. Dangl et al. (2008) develop a model in which a portfolio manager is hired by a management company which can fire him as a response to poor performance and investors can move capital in and out of the fund. The model rationalizes the positive relation between manager tenure and fund size and the increase of portfolio risk before a manager replacement and the following risk decrease. Finally, Malliaris and Yan (2010) link the skewness of the fund strategies with fund manager career concerns. In contrast to these papers, we provide a rich but tractable model that allows us to characterize both the investors' delegation decision and the fund manager's investment strategy. Moreover, the analysis of career concerns across the business cycle has largely been unexplored by both the theoretical and the empirical literature. As will be discussed in further detail in section 5, the combination of reputation-building motives and aggregate uncertainty leads to a set of new empirical implications.

This paper is also related to the literature on flow-performance sensitivity in the mutual fund sector. Chevalier and Ellison (1997) document a convex relationship between flows and performance, and that managers change their risk taking in line with these convex incentives. Sirri and Tufano (1998) provide evidence that this convex relationship is the result of costly search by investors. On the theory side Basak et al. (2007), Chapman et al. (2007), among oth-

ers, characterize managers' optimal portfolio choice in the context of a convex flow-performance relationship. I model performance-flow elasticities endogenously and consider how these might distort managers' incentives.

A growing strand of the literature employs continuous time techniques to find optimal contracts in dynamic principal-agent relationships (DeMarzo and Sannikov (2006), Sannikov (2008), Biais et al. (2007), He (2009)); to characterize the equilibrium in games of imperfect public monitoring (Sannikov (2007) and Sannikov and Skrzypacz (2010)); to analyze the capital structure of the firm (DeMarzo and Sannikov (2006) and Bolton et al. (2011)), to analyze financial frictions in macro general equilibrium models (Brunnermeier and Sannikov (2012), He and Krishnamurthy (2008) and He and Krishnamurthy (2012)) and to provide a recursive characterization of equilibria in reputation games (Faingold (2005), Board and Meyer-ter Vehn (2010) and Faingold and Sannikov (2011)). Methodologically, Faingold and Sannikov (2011) whose focus is on the characterization of the conditions guaranteeing a unique equilibrium outcome, is the most closely related paper to this one. However, we extend their analyses by including the possibility of aggregate uncertainty and by explicitly characterizing equilibrium behavior.

Finally, our results might also shed some light on the behavior of financial advisors which, since Campbell (2006), has attracted economists' attention (Bolton et al. (2007) and Inderst and Ottaviani (2009)). In contrast with the existing literature, we provide a dynamic model in which the opportunity to build a reputation distorts the manager's incentive by inducing him to manipulate the projects he invests in, the exposure to tail risk and amplification of aggregate shocks. The model can be applied to understand how financial advisors were able to steer riskier loans to their customers during the recent housing boom.[2]

In the next section, I show how market discipline shapes managers' behavior. In section 3, I introduce aggregate uncertainty to capture booms and crises and to show that market discipline induces managers to exacerbate aggregate fluctuations. To conclude, in section 4, I review empirical evidence of the model's testable predictions and discuss potential extensions.

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[2] Investment Company Institute reports that 73% of investors consult financial advisors for 401(k) plans, mortgages and investments. However, in many cases they have conflicting interests: "Many customers appear to have been encouraged to take out loans by brokers more bothered about their fees than their clients' ability to repay their debts" (*The Economist*, March 24, 2007).

3.2 The Basic Model

Overview. I propose a continuous-time model with two classes of agents, investors and specialists. The specialist has the technology or the know-how to invest in a risky asset, which the investors cannot directly invest in. Then, the specialists can be compensated from the investors in order to invest in the risky asset on the investors' behalf. In terms of the banking models, we can think of the specialist as the manager of a financial intermediary which raises financing from the investors. The key friction is that this intermediation relationship is subject to a moral hazard problem, i.e. the returns of the risky asset crucially depend on the specialist's actions. While the existing literature has focused on optimally designing the contract between the two classes of agents to mitigate the moral hazard problem, our model analyzes the effect that reputation concerns have on the specialists' actions.

Setup. We consider an economy with a risk-neutral specialist facing a continuum of risk neutral investors in a continuous-time repeated game. At each time $t \in [0, \infty)$, each investor $i \in I \triangleq [0, 1]$ chooses the fraction of their unit wealth $k_t^i \in [\underline{k}, 1]$ to invest with the specialist, while the remaining fraction $1 - k_t^i$ is invested in a safe security at rate s. The lower bound $\underline{k}$ can be interpreted as the fraction of funds invested that are not easily or costless to withdrawn. The specialist invests in a strategy that is subject to idiosyncratic diffusion risk, and whose per dollar returns are

$$dR = a_t dt + \sigma dZ \tag{3.1}$$

where $a_t \in [0, 1]$ is an unobserved action that the specialist takes at each point in time, while $(Z_t)_{t \geq 0}$ is a Brownian motion and σ is the volatility of returns. We write $(\mathcal{F}_t)_{t \geq 0}$ to denote the filtration generated by $(R_t)_{t \geq 0}$. Then, $(R_t)_{t \geq 0}$ is a noisy public signal whose evolution depends on the effort choice a_t. The assumption that only the drift of R depends on the specialist's action corresponds to the constant support assumption that is standard in discrete time repeated games, and it is without loss of generality to assume that the specialist's action affects the drift of the strategy returns (3.1) linearly.[3] Moreover, we do not allow the specialist to directly influence the returns volatility σ as otherwise his action would become immediately

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[3] By Girsanov's theorem the probability measures over the paths of two diffusion processes with the same volatility but different bounded drifts are equivalent, that is, they have the same zero-probability events.

observable.

Action a_t can have different interpretations. First, it can be interpreted as the specialist's effort in picking the right stocks to invest in, i.e. his effort in acquiring information on the companies to invest in if (3.1) is a value strategy. Second, we can think of a_t as the probability with which the specialist suggest the best products given the preferences of his clientele, i.e. a lower a means that the specialist is more prone to sell the products on which he gains higher commissions irrespective of his investors' preferences.[4] Finally, the model is isomorphic to a setup in which the specialist can divert cash flow as assumed in the dynamic contracting literature (see DeMarzo and Sannikov (2006) and Biais et al. (2007)).

In this section, we assume that the investors are anonymous: at each time t the public information includes the aggregate distribution of the investors' actions $\bar{k}_t$, which capture the assets under management at time t, but not the action of any individual investor. This is meant to capture the fact the investors are dispersed and they cannot write an explicit contract with the specialist as in the retail asset management industry. Therefore, the specialist must rely on its reputation to induce investors to allocate capital to his fund.

Contracts and Payoffs. Contracts can be described by two parameters: a management fee f and a performance fee γ. We assume that both are fixed characteristics of the fund. Management fee is restricted to be non-negative and is a per-dollar managed fee. The performance fee is symmetric: for example, at instant t the specialist has a return R_t, his compensation will be $\gamma (R_t - f) + f$ per dollar managed. Whereas the investors would receive $(1 - \gamma) (R_t - f) - f$.

Investors have identical preferences, and by investing a fraction k_t^i of capital with the specialist, each investor i receives the following flow payoff at time t:

$$u \left(a_t, k_t^i \right) = k_t^i ((1 - \gamma) (R_t - f) - f) + \left(1 - k_t^i \right) s$$

Then, at each point in time, the investors have one unit of capital to invest, and decide the fraction to invest in the fund and the fraction allocated to the safe asset, anticipating that the returns of the fund depend on the specialist's effort choice a_t.

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[4]More precisely, as in the credence good literature (see among others Pesendorfer and Wolinsky (2003) and Bolton et al. (2007)) his action a_t is the effort spent in matching the investors preferences with the financial products. The signal R_t might be the returns of the products suggested or the utilities derived by the investors and σ can capture the transparency of the market.

Given the aggregate investment strategy $\bar{k}$, the specialist obtains the following flow payoff

$$\pi\left(a_t, \bar{k}_t\right) = \bar{k}_t \left(\gamma \left(R_t - f\right) + f\right) + \left(1 - a_t b\right) \bar{k}_t - ca_t$$

where the parameter $b \in (\gamma, 1)$ captures the degree of misalignment between the two agents. That is, there exists a conflict of interest between the specialist and the investors, in that a specialist might suggest certain financial products instead of others, to gain additional broker fees if those products are sold. As discussed in the introduction, this possibility has gained particular attention recently during the financial crisis with subprime mortgages sold to investors that were instead eligible for the prime market.[5] The parameter b might also capture the private benefits that accrue to the specialist by diverting the funds in other privately optimal strategies.

While an specialist has a higher incentive to mislead his customers as the capital invested raises, he might incur in additional costs that are unrelated to the capital managed, as captures by the parameter $c \geq 0$. This cost might capture, for example, the information acquisition cost paid by the specialist to identify the profitable trades.

Information Structure. While the investors' payoff is common knowledge, there is uncertainty about the type θ of the specialist. At time $t = 0$ investors believe that with probability $p \in (0,1)$ the specialist is a behavioral type ($\theta = B$), who always chooses action $\tilde{a}$, and that with probability $1 - p$ the specialist is strategic ($\theta = S$), and maximizes the expected value of his profits. This is meant to capture the idea that investors are not aware of the incentives that the specialist is facing, for example they do not know if there are products the specialist would prefer to steer to his customers. The behavioral type can be thought as the specialist who has no conflict of interest $b = 0$, who then chooses $\tilde{a} = 1$. Moreover, these incentives are persistent, which means that the specialist has the opportunity to build a reputation for honestly managing his customers' funds.

Even if managers and investors observe the fund returns $(dR_s, s \leq t)$ before choosing a_t and k_t, for the purpose of specialist's and investors' decision problems, the history of fund returns can be summarized in the specialist reputation p_t.

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[5] In a comment on the causes of the current subprime mortgage crisis, *The Economist* observes that "many customers appear to have been encouraged to take out loans by brokers more bothered about their fees than their clients' ability to repay their debts" ("The trouble with the housing market," March 24, 2007, 11).

Strategies and Equilibrium. A public strategy of the specialist is a random process $(a_t)_{t\geq 0}$ with values in $[0,1]$ and progressively measurable with respect to $(\mathcal{F}_t)_{t\geq 0}$. Similarly, a public strategy of investor i is a progressively measurable process $(k_t^i)_{t\geq 0}$ taking values in $[0,1]$. In the repeated game the investors formulate a belief about the specialist's type following their observations of $(R_t)_{t\geq 0}$. A belief process is a progressively measurable process $(p_t)_{t\geq 0}$ taking values in $[0,1]$, where p_t denotes the probability that the investors assign at time t to the specialist being the behavioral type:

Definition 22 *A public sequential equilibrium consists of a public strategy profile $(a_t)_{t\geq 0}$ of the strategic specialist, a public strategy $(k_t^i)_{t\geq 0}$ for each investor i and a belief process $(p_t)_{t\geq 0}$ such that at all time $t \geq 0$ and after all public histories,*

1. the strategy of the specialist maximizes his expected payoff

$$\mathbb{E}_t\left[\int_0^\infty re^{-rs}\pi\left(a_s, \bar{k}_s\right)ds \mid \theta = S\right],$$

2. the strategy of each investor i maximizes his expected payoff

$$p_t\mathbb{E}_t\left[\int_0^\infty re^{-rs}u\left(\tilde{a}, k_s^i\right)ds \mid \theta = B\right] + (1-p_t)\mathbb{E}_t\left[\int_0^\infty re^{-rs}u\left(a_s, k_s^i\right)ds \mid \theta = S\right]$$

3. beliefs $(p_t)_{t\geq 0}$ are determined by Bayes' rule given the common prior p_0.

A strategy profile satisfying condition (1) and (2) is called sequentially rational. A belief process satisfying condition (3) is called consistent.

We can simplify the above definition in two ways. First, because the investors have identical preferences, we shall work with the aggregate strategy $\left(\bar{k}_t\right)_{t\geq 0}$ rather than with the individual strategies $\left(k_t^i\right)_{t\geq 0}$. Second, since the behavior of any individual investor is not observed by any other player in the game and it cannot influence the evolution of the public signal, the investors' strategies must be myopically optimal. Thus, we will say that a tuple $\left(a_t, \bar{k}_t, p_t\right)_{t\geq 0}$ is a public sequential equilibrium when, for all $t \geq 0$ and after all public histories, conditions (1) and (3) are satisfied as well as the myopic incentive constraint

$$k \in \arg\max_{k'\in[0,1]} p_t u\left(\tilde{a}, k_t'\right) + (1-p_t)u\left(a_t, k_t'\right)$$

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Finally, note that for both pure- and mixed-strategy equilibria, the restriction to public strategies is without loss of generality. For pure strategies, it is redundant to condition a player's current action on his private history, as every private strategy is outcome-equivalent to a public strategy. For mixed strategies, the restriction to public strategies is without loss of generality in repeated games with signals that have a product structure, as in the repeated games that we consider. To form a belief about his opponent's private histories, in a game with product structure a player can ignore his own past actions because they do not influence the signal about his opponent's actions.

3.3   Analysis

In this section we develop a recursive characterization of public sequential equilibria which is used through the rest of the paper. Lemma 1 and lemma 2 are intermediate steps, which characterize the evolution of investors' beliefs and the specialist's Hamilton-Jacobi-Bellman (HJB) equation. Theorem 1 is the main result of this section, it describes the equilibrium behavior of specialist and investors and the resulting dynamics. Proposition 1 complement the characterization of the equilibrium by showing few basic properties of the specialist equilibrium value function. Next section is devoted to the comparative statics with respect to the main parameters of the model.

A natural state variable in our model is the investors' belief p about the specialist's type. We start by characterizing the stochastic evolution of the investors' posterior beliefs on and off-equilibrium path in the following lemma.

Lemma 23 (Belief Consistency) *Fix the prior $p_o \in [0, 1]$ on the commitment type. A belief process $(p_t)_{t \geq 0}$ is consistent with a public strategy profile $(\hat{a}_t, k_t)_{t \geq 0}$ if and only if*

$$dp = \left[\chi \left(\tilde{a}, \hat{a}, p \right) \left(a - \bar{a} \left(p \right) \right) / \sigma \right] dt + \chi \left(\tilde{a}, \hat{a}, p \right) dZ^p \qquad (3.2)$$

where for each $(\hat{a}, p) \in [0, 1]^2$,

$$\chi \left(\tilde{a}, \hat{a}, p \right) \triangleq p \left(1 - p \right) \sigma^{-1} \left(\tilde{a} - \hat{a} \right)$$

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$$\bar{a}(p) \triangleq p\widetilde{a} + (1-p)\hat{a}$$

Note that in the statement of Lemma 1, $(\hat{a}_t)_{t\geq 0}$ is the strategy that the investor believes that the unskilled specialist is following. Thus, when the specialist deviates from his equilibrium strategy, the deviation affects only the drift of $(R_t)_{t\geq 0}$, but not the other terms in equation (3.2), in fact, unexpected changes in the observation process cannot raise volatility, since they are unobserved.

Equation (3.2) emphasizes the two separate forces which drive the updating. The drift term $\chi(\widetilde{a}, \hat{a}, p)(a - \bar{a}(p))/\sigma dt$ takes into account the possibility that the specialist deviates from the expected effort choice. In expectation this term is zero, i.e. $E(a) = \bar{a}(p)$, however this is useful in the computation of the optimal action for the strategic advisor. The diffusion term in (3.2) captures instead the influence of the observed signal on the evolution of beliefs. Z^p being a Brownian motion, this part of the updating is completely unpredictable. Intuitively, this expresses the fact that the current belief already incorporates everything that there is to know, so any change must come as a surprise. The representation

$$\sigma dZ^p = a_t dt + \sigma dZ_t - (p_t \widetilde{a} + (1 - p_t)\hat{a}_t)\, dt$$

confirms this, showing that the change in beliefs depend on the difference between the realized signal $a_t dt + \sigma dZ_t$, and the expected signal $\bar{a}(p)\, dt$.

The coefficient $\chi(\widetilde{a}, \hat{a}, p)$ of equation (3.2) is the volatility of beliefs: it reflects the speed with which the investor learn about the type of the specialist. The lower the noise level σ, or larger the difference between the drifts produced by the two types, the more informative is the signal and the more pronounced is the change of beliefs after the signal is observed. This is relevant of course only if the investors are not certain of the current type. For $p = 0$ or 1, the investors rule out any possibility of learning from the signal, i.e. the diffusion term vanishes no matter which action is taken. Once investors are certain about the specialist's type, their beliefs are not sensitive to his performance anymore.

We turn to the analysis of the specialist's problem. Since we are looking for an equilibrium that is Markovian in the investors' belief, we derive his HJB equation as a function of the belief

p. The specialist's problem is to find a policy function $a\left(p_t\right)$ so as to solve the following problem

$$V\left(p\right) \triangleq \max_{a:[0,1]\to[0,1]} V\left(a,p\right)$$

subject to the stochastic evolution of beliefs p derived in Lemma 1 and $a_t \triangleq a\left(p_t\right)$. The following lemma derives the specialist's value function a function of investors' beliefs p.

Lemma 24 (HJB Equation) *Given the investor's beliefs p, investor's strategy k and the expected action $\hat{a}$, the specialist's HJB equation is given by*
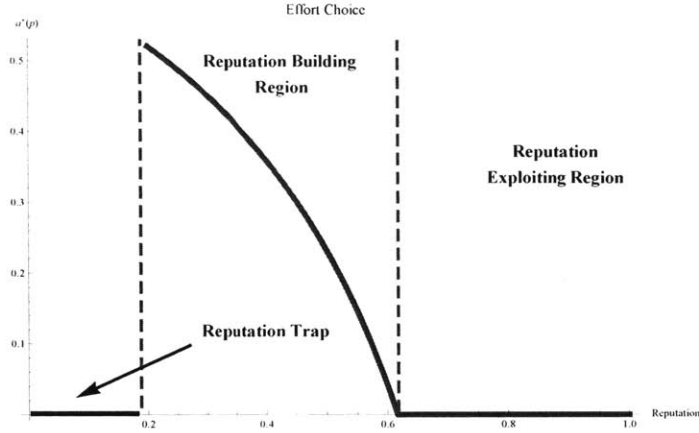
$$rV\left(p\right) = \max_{a\in[0,1]} r\pi\left(a,\bar{k}\right) + \frac{\chi\left(\widetilde{a},\hat{a}_t,p_t\right)}{\sigma}\left[a - \bar{a}\left(p\right)\right]V'\left(p\right) \tag{3.3}$$
$$-\frac{\chi\left(\widetilde{a},\hat{a}_t,p_t\right)^2}{\left(1-p\right)}V'\left(p\right) + \frac{\chi\left(\widetilde{a},\hat{a}_t,p_t\right)^2}{2}V''\left(p\right)$$

The specialist's value function has an intuitive interpretation. When choosing which products he is going to offer to his clients, or the composition of its portfolio, the specialist maximizes the sum of his flow payoff and his continuation value, taking into account how his decision a affects the learning of the market about his type and the resulting impact on his reputation. That is, he weights the myopic benefits of lowering the optimal action a, against the change in his value function $V'\left(p\right)$ due to the market's updating about his type θ. Specifically, exerting higher effort, allows the specialist to capture higher incentive fees γ, but doing so prevents him from capturing the broker fees b. This trade-off describes his flow payoff. However, what prevents the specialist from completely exploiting his position is that a lower a and the consequent poor performance adversely affects his reputation p, which in equilibrium results in lower investment k in the future.

To show how these different forces play out in equilibrium, we now turn to the conditions that characterize sequential rationality. The investors' problem is straightforward, in fact, since they are anonymous, they cannot do any better than maximize their myopic payoff:

$$k \in \arg\max_{k'\in[0,1]}\left[\left(k'\left(1-\gamma\right)\left(\bar{a}\left(p_t\right)-f\right)-f\right)+\left(1-k'\right)s\right]$$

where recall that $\bar{a}\left(p\right) = p_t\widetilde{a}+\left(1-p_t\right)\hat{a}_t$ is the expected returns of the investment as a function

Effort Choice

Reputation Building
Region

Reputation
Exploiting Region

Reputation Trap

Reputation

of the expected effort level $\hat{a}$. Notice that this is obviously true even when the specialist is facing a sequence of short-lived investors, in our setup the specialist is facing a continuum of investors, and because each investor i is too small to have an impact on the equilibrium of the game and on the specialist's continuation value his action must be myopically optimal.

The specialist's problem is significantly more complex, because when optimizing he takes into account the effect that his action at time t has on the investors beliefs, which changes his continuation value. A public strategy $(a_t)_{t \geq 0}$ is sequentially optimal if for all $t \geq 0$ and after all public histories

$$a_t \in \arg \max_{a' \in [0,1]} \bar{k}_t (\gamma - b) a' - ca' + \frac{\chi (\tilde{a}, \hat{a}_t, p_t)}{r\sigma} V'(p) a'$$

This condition characterizes the optimal specialist's effort choice as a function of the belief p and of the reputational sensitivity $\Lambda \triangleq \frac{\chi(\tilde{a}, \hat{a}_t, p_t)}{r\sigma} V'(p)$. The latter measures how important for the specialist is his continuation value. Higher reputational value Λ and higher is the effort exerted by the specialist. Intuitively, the specialist will exert higher effort when the benefit $V'(p)$ of doing so is higher, that is when his future payoff is more sensitive; when the market is more transparent, i.e. low σ, and when he is more patient lower r. The incentives to imitate the behavioral type are weaker when the investors are more convinced about the specialist's type, that is, when p is close to zero and one.

Now we can characterize the equilibrium. Since effort is costly for the specialist and the investors' payoff is linear in the expected effort $\bar{a}$, the specialist will choose the lowest value of

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a that makes the investors choose a positive level of capital k. Call this value $a^*(p)$, this effort choice can then be substituted in the first order condition for the specialist in order to pin down the level of capital $k^*(p)$ that makes it incentive compatible for the specialist to exert the effort level $a^*(p)$. The strategy profile $(a^*(p), k^*(p))$ can then be substituted in the specialist's HJB equation (3.3) in order to get a second-order differential equation in p.

We can now state the main result of this section

Theorem 25 (Equilibrium) *If $c = 0$, there exists two regions defined by a single cutoff value $\bar{p}$ such that*

$$For\ p < \bar{p},\ (a^*, k^*) = \left(\frac{f + s + f(1 - \gamma)}{(1 - \gamma)(1 - p)} - \frac{p}{(1 - p)}\widetilde{a}, \frac{\Lambda}{(b - \gamma)} \right)$$

$$For\ p > \bar{p},\ (a^*, k^*) = (0, 1)$$

If c is sufficiently small, there exists a unique cutoff $\underline{p} < \bar{p}$ such that $(a^*, k^*) = (0, \underline{k})$ for every $p \in [0, \underline{p}]$.

The dynamics of the equilibrium effort choice is depicted by figure 1 as a function of the specialist's reputation. First, when investors are not going to respond to good performance, the specialist's continuation value becomes insensitive to his performance, which in turn dampens specialist's incentive to exert effort. Lower expected effort leads investors to allocate a lower fraction of their capital to the fund, up to the point in which they do not find it worthwhile to invest at all. That is, there exists a reputation trap: the specialist does not exert effort because his cost of doing so is higher than the positive impact on his continuation value. The existence of this reputation trap relies on the fact that the specialist pays a positive cost of exerting effort, which is not proportional to the capital invested with the specialist.

Notice that even if in expectation the specialist is not going to exit the trap, because the investors' beliefs have a negative drift, which means that in the long-run specialist's reputation converges to zero, after a sufficiently long series of good performance, specialist's reputation can go back above the threshold. That is, since performance is noisy and subject to shocks, his reputation can increase enough that investors find it optimal to invest again with the specialist.

Second, for intermediate reputation values there exists a reputation building region, where

the specialist exerts positive level of effort, which allows him to imperfectly mimic the choice of the commitment type. Higher effort increases the expected returns and incentivizes the investors to allocate a positive fraction of their capital to the fund. This is where we expect most of the funds to be. Good performance positively affects reputation, because investors are still uncertain about the specialist's type, which means that their choice k will be sensitive to the observed returns. This in turn incentivizes the specialist to exert effort over time.

Finally, when the reputation is sufficiently high, a positive level of effort is not sustainable in equilibrium, because the investors are willing to delegate their capital even if they expect zero effort from the strategic specialist. Intuitively, when his reputation is sufficiently high, the specialist starts behaving more myopically extracting in this way more surplus from the relationship with the investors. That is, there exists a reputation exploitation region. This region corresponds to the case of a fund which has already gained the "star status", which allows the specialist to attract more investors, because of his past performance, and his current performance becomes less important for the investors' choice. That is, the specialist is rewarded with capital inflows, even if his performance does not outperform the relevant benchmarks.

One could interpret the equilibrium in this region in light of the recent scandals. Fund managers such as Bernie Madoff or financial advisors such as those at Washington Mutual or Goldman Sachs, had the opportunity to deceive their clients, because they were able to gain the trust of the market.

To complete our characterization of the equilibrium we show the following result:

Proposition 26 *There exists a unique bounded value function $V(p)$, which is increasing in the investors' belief p, and decreasing in the volatility σ and in the conflict of interest b, which solves the specialist HJB.*

This result ensures the existence of a solution to the HJB equation, and highlights the effects of the main parameters of the model on the equilibrium payoff of the strategic specialist. First thing to notice is that this is a model in which reputation is good, that is, allows the specialist to (at least imperfectly) commit to the efficient action, this explains why his equilibrium payoff is increasing the reputation p. Intuitively, the equilibrium payoff of the specialist is increasing in his reputation, because as shown in the previous result, higher reputation means that the

Value of Reputation
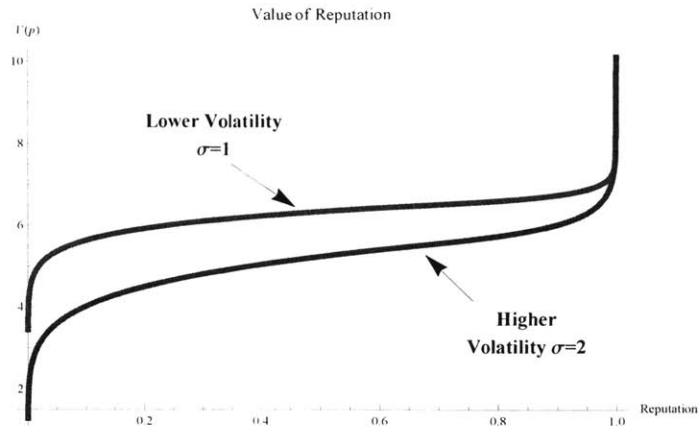
specialist attract more funds and at the same time irrespective of his effort choice the fund looks more attractive to the investors.

It is interesting to analyze how the equilibrium payoff of the specialist is affected by the volatility of returns. Figure 2 shows that higher volatility, or equivalently lower market transparency, reduces the specialist's equilibrium payoff. The main channel is how the volatility σ affects investors' learning. Higher σ means that it will be more difficult for the specialist to increase his reputation, because positive returns will be interpreted as the result of luck rather than of his effort.

Finally, since b is the main parameter capturing the severity of moral hazard, it is interesting to analyze how an increase in the severity of moral hazard might affect the specialist's ability to gain profits. Proposition 1 shows that a higher conflict of interest with the investors reduces the equilibrium payoff of the specialist, because it becomes more costly for the specialist to take the long-term optimal action. This adversely affects the investors' optimal investment policy k.

3.3.1 Equilibrium Properties

We can now investigate further the properties of this equilibrium with a series of results on the equilibrium dynamics and comparative statics on a^* and k^*. One of the main advantages of having a continuous time framework is the greater flexibility in characterizing the effect of the parameters of the model on the equilibrium outcome.

One striking feature of the asset management industry is the extreme persistence and very low variation in the charging fees. Then, understanding how a potential change in the fees
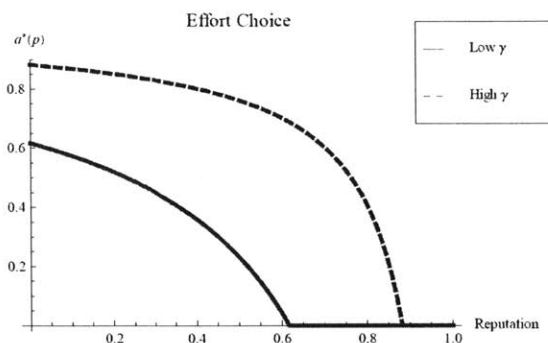
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Figure 3-1: Managers' action as a function of their reputation and for different performance fees.

can be informative to understand how specialist's incentives are shaped and how this formal incentives interact with his objective to build a reputation. We are interested in addressing the following questions. First, how contracting features affect the equilibrium effort choice?

Property 1 For $p \in [\underline{p}, \bar{p}]$, the specialist's action is decreasing in the market's belief p and it increases with the fees f and γ and with the investor's outside option s.

First, as depicted in figure (3-1), managers' incentives to deceive investors are increasing in the reputation he has built. However, this effect is mitigated by the possibility of the investors to choose a different safe investment s, and by the performance fee γ. Intuitively, the fees f and γ measure how much the advisor cares about the returns, and then in some sense how close his interests are aligned with those of the investors. The effect of the investors' outside option is driven by the necessity for the specialist to exert more effort in order to compensate the investor for the lost opportunity s. The effect of reputation p captures the idea that at high reputation level the specialist has higher incentive to deceive the investors.

We turn next to the effect of market characteristics on the equilibrium dynamics of figure 1. In particular, how does the returns volatility affect the possibility to end up in a reputation trap?

Property 2 The threshold $\underline{p}$ is increasing in the cost of effort c, in the market volatility σ and specialist's patience r.

This result shows that the region supporting the reputation trap widens as the level of transparency in the market decreases, because the specialist expects his action to be less effective

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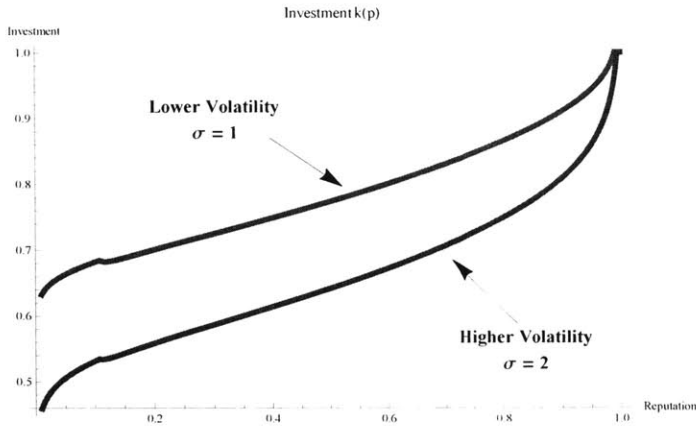
in influencing the investors' beliefs, which means that effort is less productive. Moreover, as r increases the specialist cares more about the cost of effort exerted at time t, which also lowers his incentive to exert positive level of effort.

Finally, we can characterize how investors react to information about the specialist's performance.

Property 3 The optimal investment k is increasing in the specialist's reputation p, while it decreases in σ and b.

These comparative statics results are quite interesting. Even if the investors are risk-neutral, they are less willing to invest in a very volatile environment, i.e. high σ, because it is more difficult to discipline the specialist. But as the specialist's reputation increases, the investor's expected payoff increases which makes him more willing to allocate his wealth to the fund (higher k). Moreover, as the conflict of interest b increases, the weight investors assign to reputation is lower which makes them invest less. The two parameters σ and b can be interpreted as two different aspects of the moral hazard problem. While b captures how strong the incentive for the specialist is to manipulate his returns, the volatility σ captures investors' ability to monitor the specialist.

We can relate this result to some recent empirical evidence on inflows in the asset management industry. Huang et al. (2011) analyze mutual fund data over 1993-2006, show that flow sensitivity to past performance is weaker for funds with more volatile past returns. Moreover, older funds have a weaker sensitivity of flows to performance than younger funds.

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Barber et al. (2005) find negative relations between flows and front-end-load fees. Not about behavioral biases but due to conflict of interest. Load funds are distributed by brokers or financial advisors, and the fees as proxy of conflict of interest.

3.4 Tail Risk and Flight to Safety

In the previous section the only source of risk is given by the strategy idiosyncratic risk σdZ. However, the financial crisis has highlighted the importance played by tail risk. It has also raised the question of why financial intermediaries who have the knowledge to discern this type of risks got so exposed to it. We are going to provide a rationale for this behavior based on the expectation that when these rare events happen they affect the specialists' continuation value, which in turn changes their incentives to acquire information about these rare events and their strategies in the first place.

We introduce a friction between investors and the specialist: investors cannot understand if managers have piled up tail risk in their portfolio, that is, they cannot discern if the returns generated by the specialist are due to the superior skill of the specialist or because the specialist has strategically exposed the investors' funds to these additional risks. Specifically, we assume that the strategy (3.1) is subject to a jump-event risk dN_t with size $\zeta \in \{\zeta_L, \zeta_H\}$ with $\zeta_H \geq 0 > \zeta_L$ The specialist chooses the exposure $e \in [0,1]$ to the jump-event risk and the return equation then becomes

$$dR = (a_t + e_t\gamma)dt + \sigma dZ + e_t\zeta dN_t \tag{3.4}$$

where $e_t\gamma$ is a premia component that depends on the manager's portfolio choice, i.e. a premia $\gamma > 0$ that the specialist earns for holding market-wide tail risk. The aggregate jump event is realized at random time τ_φ which is a Poisson arrival process with intensity φ. On event realization the market wide jump state ζ becomes public knowledge.

We assume that skilled specialists know if $\zeta = \zeta_H$ or $\zeta = \zeta_L$, which means that they will choose $e_t = 1$ if and only if the strategy has positively skewed returns ($\zeta = \zeta_H$). We allow the unskilled specialist to acquire such information at a cost c_ζ, that is, if he pays the cost he knows the size of the jump-event at time $t < \tau_\varphi$. The jump event can capture for example the possibility of a fall in housing prices and (3.4) is the returns of the investment in the real estate

market. The cost c_ζ can capture the cost of analyzing the data or the cost of designing financial instruments able to isolate the investors from such events. The assumption that investors cannot understand if the returns come from exposure to tail risk or from the alpha-generating skill of the specialist might capture the complexity of the financial instruments employed.

In order to understand what the optimal strategy of the unskilled specialist is we need to analyze the equilibrium in the case that the jump-event is realized. The realization of the jump can be an instance in which the investors are able to perfectly learn the type of the specialist, if the two types of specialists take on different strategies. In fact, if the strategy turns out to be more profitable than expected ($\zeta = \zeta_H$) but the investors do not capture any of those returns, this means that the specialist is unskilled because missed the opportunity of extra returns. On the other hand, if the returns turn out to be negatively skewed ($\zeta = \zeta_L$), and investors incur in a loss then they will infer that the unskilled specialist did acquire the information needed to make the optimal decision. Such events usually trigger a sharp reaction of investors such "flight to safety" or "flight to liquidity". We are going to assume that if $\zeta = \zeta_L$ there is a flight to safety event which in the model can be captured by assuming that investors set $k = \underline{k}$, i.e. during these periods investors minimize their exposure to risky assets and invest all their resources into safe securities. This happens if for example ζ_L is very big and persistent.

Now we can analyze the dynamics before the realization of the jump event. The possibility to provide extra returns by exposing the investors' fund to tail risk allows the specialist to boost his reputation if $e_t > 0$. That is, there exists a substitutability between the effort a_t in picking the right investment strategy and the exposure to tail risk.

We can show the following result

Proposition 27 *If there is a flight to safety when $\zeta = \zeta_L$, the unskilled specialist does not acquire information about the jump event but expose the investors to tail risk, i.e. $e_t = 1$. Moreover, for any $t < \tau_\varphi$ his effort choice is lower than when there is no jump-event risk.*

The previous proposition shows two main results. First, even when the specialist has the possibility to acquire information about jump events, he can decide not to do so. The intuition is as follows: in the event of a negative jump the specialist is going to lose the investors' support independently from his behavior, which increases his incentive to misbehave before such events.

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If instead the returns turn out to be positively skewed, he is rewarded with extra funds from investors. Then, it is optimal to save the costs c_ζ of insulating the portfolio from such tail risk. Second, the possibility of the jump event ζ allows the specialist to improve his reputation by capturing the premium γ due to tail risk. Moreover, since investors cannot distinguish between the different sources of returns, the agency cost becomes bigger as the specialist can exert lower effort than in absence of tail risk.

Intuitively, when the crisis are expected to be severe and persistent so that investors decide to allocate their resources exclusively to the safe assets, specialists strategically choose to get over exposed to tail risk due to their reputation concerns. Then, market discipline instead of incentivizing the specialist to protect the investors from fluctuations actually makes the investors more vulnerable to these events.

3.4.1 Aggregate Uncertainty

We assume only two possible states of the economy $\omega_t \in \{\mathcal{N}, \mathcal{C}\}$. That is, the agents can interact in normal times, $\omega = N$, or during a crisis, $\omega = C$. We assume that $\sigma_C > \sigma_{\mathcal{N}}$, i.e. there is evidence that during recession volatility is higher: stock market volatility is almost 30% higher during NBER- dated recessions than during NBER expansions, and $\mu_{\mathcal{N}}(a) > \mu_C(a) \; \forall a$, in particular we can assume $\mu_{\mathcal{N}}(a_t) = a_t + \pi > a_t = \mu_C(a_t)$ where $\pi \in (0,1)$.[6]

What this assumption is meant to capture is that during normal times not matter what the specialist does, the returns are higher than during a crisis. In other terms, his effort choice is much more important in a crisis, rather than in normal times, as the severity of the crisis π increases. Then, returns during a crisis are lower and more volatile.

To capture the idea that periods of booms are followed by recession times, we assume that the economy fluctuates between these two states. In particular, the aggregate state of the economy at time t is constant if there has been no shock in $[0, t]$ then $\omega_t = \omega_0$. The state changes

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[6]We can assume different specification, for example: $\mu_{\mathcal{N}}(a_t) = a_t > \pi a_t = \mu_C(a_t)$, that is, booms are periods in which the productivity of the specialist's effort is higher. This would yield similar results.

according to a continuous time Markov process with the following transition probabilities

$$\Pr\left(\omega_{t+dt} = \mathcal{N} \mid \omega_t = \mathcal{N}\right) = 1 - \lambda_{\mathcal{N}} dt + \circ\left(dt\right),$$

$$\Pr\left(\omega_{t+dt} = \mathcal{C} \mid \omega_t = \mathcal{N}\right) = \lambda_{\mathcal{N}} dt + \circ\left(dt\right),$$

$$\Pr\left(\omega_{t+dt} = \mathcal{N} \mid \omega_t = \mathcal{C}\right) = \lambda_{\mathcal{C}} dt + \circ\left(dt\right),$$

$$\Pr\left(\omega_{t+dt} = \mathcal{C} \mid \omega_t = \mathcal{C}\right) = 1 - \lambda_{\mathcal{C}} dt + \circ\left(dt\right),$$

where $\lambda_\omega \geq 0$ ($\omega = N, C$) are the arrival rates known to all market participants.[7] The arrival rate of these shocks is independent of the signal $(R_t)_{t \geq 0}$.

We can show the following result:

Theorem 28 *The Effort choice is procyclical, i.e. $a_{\mathcal{N}}^* > a_{\mathcal{C}}^*$, and $\bar{p}_{\mathcal{N}} > \bar{p}_{\mathcal{C}}$ if and only if* $s_{\mathcal{N}} - s_{\mathcal{C}} > \pi\left(1 - \gamma\right).$

The specialist exploits his reputation sooner in a crisis, because fund is relatively more attractive for the investors. If

$$\frac{V'_{\mathcal{N}}\left(p\right)}{\sigma_{\mathcal{N}}} > \frac{V'_{\mathcal{C}}\left(p\right)}{\sigma_{\mathcal{C}}} \Rightarrow k_{\mathcal{N}}^* > k_{\mathcal{C}}^*$$

which is true for $\pi, \lambda \to 0$. Investors are more willing to invest in a boom because they can monitor the specialist better.

What happens to $\underline{p}$? We have higher volatility in a crisis, so if this is the only effect we also have higher reputation traps. Then, the interval in which the specialist is exerting higher effort shrinks. However, there is also the effect of V'. It seems the same condition as with the investment.

3.5 Empirical Implications and Discussion

We have proposed a framework to analyze the behavior of specialists who manage investors' funds and are compensated with a fixed fraction of the asset under management and a fraction

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[7]See Karlin and Taylor (1986, p.146).

of the realized returns, but their strategies are mainly driven by implicit incentives. The model is able to provide a rich set of testable implications. First, in contrast to the existing literature on career concerns, our model predicts that the performance history of fund managers has a significant impact on their future behavior. This can be tested by looking at how past performance affects their portfolio holdings.

Second, the strategies adopted by fund managers crucially depend on their reputation and on the market volatility. This implies a testable cross-sectional variation across managers with different histories. In particular, managers with lower reputation should increase the riskness of their portfolio hoping to improve their status by realizing higher returns. At the same time managers with higher reputation tend to underperform in periods of high volatility but suffer lower outflows, due to the slow investors' learning. Third, the portfolio returns of fund managers with low reputations should become more and more skewed as the risk of a crisis or of a flight to safety episode becomes more important.

However, the model analyzed in the previous section abstract from a number of important features of reality. I discuss below how the basic environment can accomodate such features and how these would change the results.

Management fees. In the baseline version of the paper we take the contract between the specialist and the investors as given for several reasons. First, the performance fee aligns the specialist's and the investors' interests except that for the reputation concerns of the specialist. In reality, intermediaries' contracts usually entail a fixed fraction of the asset under management and a performance fee and there is evidence of persistence in these contracts. Second, we can endogenize the fees by allowing competition among intermediaries or by assuming that investors can bargain with managers upon the fees at some discrete interval of time. This would not affect the main results. Finally, the literature has extensively examined the role of contracts and, more general, of explicit incentives in shaping managers' incentives. It might be interesting in the spirit of DeMarzo and Sannikov (2006) to analyze the optimal contract when the investors can commit at $t = 0$. In this case, there would not be any shirking in equilibrium as the specialist would be incentivized to always exert high effort. We think that while the analysis of the optimal contract generates a number of insights on the executives' compensation and how the policy maker should intervene, at the same time, the analysis of how market discipline shape

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the managers' behavior remain an important question.

Monitoring. In the model we have assumed that investors continuously observe the fund's returns which allow them to update their beliefs about the specialist's type. We could change the environment by making the returns visible only at discrete interval of time. On the one hand, this might capture the investors' inability to monitor the specialist's decisions which can be due to monitoring being costly or due to rational inattentive investors. On the other hand, how difficult it is for investors to monitor the specialist might also capture the complexity of the financial instruments employed by the specialist. This would not change the main message of the model except that for the fact that the specialist's suboptimal strategies can go undetected for longer periods of time, which can make its reputation more persistent.

Competition. We can allow the investors to search for the most performing specialist at some cost. This would endogenize the investors' outside opportunity, but would also avoid that only the specialist with the highest past performance remains active on the market. In this modified framework, the managers' exploitation region would crucially depend on the presence of other managers with higher reputation and on the investors' search costs. This would reinforce the result that during a crisis, when a higher measure of managers underperforms, agency costs are higher as the managers with a high reputation can exploit the investors' perception of their ability by not exerting effort as he does not face a strong competition.

Market prices. The basic environment abstract from the effect that managers' trades has on assets' returns. We could allow for different potential strategies whose returns are decreasing in the amount invested by fund managers. Since managers with different reputation would take on different strategies there would be an additional trade-off for the specialist: between exploiting strategies overlooked by other managers and the potential reputational cost of taking on strategies that can signal more precisely his ability.

3.6 Appendix - A

We start with some preliminaries about the specialist's value function. A public strategy profile $(a_t, k_t)_{t \geq 0}$ is an equilibrium of the game if it is a fixed point of the following non-empty correspondence $\Gamma : [0, 1] \times \mathbb{R} \rightrightarrows [0, 1]^2$ defined by

$$\Gamma(p, \Lambda) \triangleq \left\{ (a, k) : \begin{array}{l} \bar{k} \in \arg\max_{\bar{k}' \in [0,1]} \left(\bar{k}'(1 - \gamma)(\bar{a}(p) - f) - f \right) + \left(1 - \bar{k}'\right) s \\ a \in \arg\max_{a' \in [0,1]} a' \bar{k}(\gamma - b) + \Lambda a' \end{array} \right\}$$

Fix (p, Λ) and consider the following correspondence

$$\Sigma(a, k) \triangleq \left\{ \begin{array}{l} k \in \arg\max_{k' \in [0,1]} \left[(k'(1 - \gamma)(\bar{a}(p) - f) - f) + (1 - k') s \right] \\ a \in \arg\max_{a' \in [0,1]} a' k(\gamma - b) + \Lambda a' \end{array} \right\}$$

then an action profile belongs to $\Gamma(p, \Lambda)$ if and only if it is a fixed point of Σ. Fix $(a, k) \in [0, 1]^2$ and notice that the assumptions on the agents' flow payoff and on the drift of the diffusion process R_t imply that $\pi(a, k)$ and $u(a, k)$ are weakly concave and hence by Brouwer's fixed point theorem $\Sigma(a, k)$ has a fixed point. Then, the correspondence $\Gamma(p, \Lambda)$ is non-empty, which shows existence.

The proof of the existence of a solution to the ODE follows the tecniques introduced by Keller and Rady (1999) and Faingold and Sannikov (2011). We devide the proofs in three steps. First we show existence. We then show that the solution must be unique and finally we show that the unique solution must be an increasing function.

The proof of Theorem 2 relies on standard results from the theory of boundary-value problems for second-order equations (see for example de Coster and Habets, 2006). We now review the part of that theory that is relevant for our existence result.

Given a continuous function $H : [a, b] \times \mathbb{R}^2 \to \mathbb{R}$ and real numbers c and d, consider the following boundary value problem:

$$\begin{aligned} V''(x) &= H(x, V(x), V'(x)), \ x \in [a, b] \\ V(a) &= c, V(b) = d. \end{aligned} \tag{3.5}$$

Given real numbers α and β, we are interested in sufficient conditions for the previous problem to admit a C^2-solution $V : [a,b] \to \mathbb{R}$ with $\alpha \leq V(x) \leq \beta$ for all $x \in [a,b]$. One sufficient condition is called Nagumo condition, which posits the existence of a positive continuous function $\psi : [0,\infty) \to \mathbb{R}$ satisfying

$$\int_0^\infty \frac{v\,dv}{\psi(v)} = \infty$$

and

$$|H(x,v,v')| \leq \psi(|v'|), \ \forall (x,v,v') \in [a,b] \times [\alpha,\beta] \times \mathbb{R}.$$

To prove existence we use the following result, which follows from Theorems II.3.1 and I.4.4 in de Coster and Habets (2006):

Lemma 29 *Suppose that $\alpha \leq c \leq \beta, \alpha \leq d \leq \beta$ and that $H : [a,b] \times \mathbb{R}^2 \to \mathbb{R}$ satisfies the Nagumo condition relative to α and β. Then:*

(a) the boundary value problem (3.5) admits a solution satisfying $\alpha \leq V(x) \leq \beta$ for all $x \in [a,b]$;

(b) there is a constant $R > 0$ such that every C^2-function $V : [a,b] \to \mathbb{R}$ that satisfies $\alpha \leq V(x) \leq \beta$ for all $x \in [a,b]$ and solves

$$V''(x) = H\left(x, V(x), V'(x)\right), \ x \in [a,b],$$

satisfies $|V'(x)| \leq R$ for all $x \in [a,b]$.

Step 1. Existence. Since the right hand side of the ODE blows up at $p = 0$ and $p = 1$, our strategy of proof is to construct the solution as the limit of a sequence of solutions on expanding closed subintervals of $(0,1)$. Indeed, let $H : (0,1) \times \mathbb{R}^2 \to \mathbb{R}$ denote the right-hand side of the ODE and for each $n \in \mathbb{N}$ consider the boundary value problem:

$$
\begin{aligned}
V''(p) &= H\left(p, V(p), V'(p)\right), \ p \in [1/n, 1 - 1/n] \\
V(1/n) &= \underline{g}, V(1 - 1/n) = \bar{g}.
\end{aligned}
\tag{3.6}
$$

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There exists a constant $K_n > 0$ such that

$$|H\left(p, v, v'\right)| \leq K_n \left(1 + |v'|^2\right), \quad \forall \left(p, v, v'\right) \in [1/n, 1 - 1/n] \times [\underline{g}, \bar{g}] \times \mathbb{R}.$$

Since $\int_0^\infty K_n^{-1} \left(1 + v^2\right)^{-1} v \, dv = \infty$, for each $n \in \mathbb{N}$ the boundary value problem above satisfies the hypothesis of the Lemma relative to $\alpha = \underline{g}$ and $\beta = \bar{g}$. Therefore, for each $n \in \mathbb{N}$ there exists a C^2−function $V_n : [1/n, 1 - 1/n] \to \mathbb{R}$ which solves the ODE on $[1/n, 1 - 1/n]$ and satisfies $\underline{g} \leq V_n \leq \bar{g}$. Since for $m \geq n$ the restriction of V_m to $[1/n, 1 - 1/n]$ also solve the ODE on $[1/n, 1 - 1/n]$, by Lemma B1 and the quadratic growth condition above the first and the second derivatives of V_m are uniformly bounded for $m \geq n$, and hence the sequence $(V_m, V'_m)_{m \geq n}$ is bounded and equicontinuous over the domain $[1/n, 1 - 1/n]$. By the Arzela'-Ascoli Theorem, for every $n \in \mathbb{N}$ there exists a subsequence of $(V_m, V'_m)_{m \geq n}$ which converges uniformly on $[1/n, 1 - 1/n]$. Then, using a diagonalization argument, we can find a subsequence of $(V_n)_{n \in \mathbb{N}}$, denoted $(V_{n_k})_{k \in \mathbb{N}}$, which converges pointwise to a continuously differentiable function $V : (0, 1) \to [\underline{g}, \bar{g}]$ such that on every closed subinterval of $(0, 1)$ the convergence takes place in C^1.

Finally, V must solve the ODE on $(0, 1)$, since $V''_{n_k}(p) = H\left(p, V_{n_k}(p), V'_{n_k}(p)\right)$ converges to $H\left(p, V(p), V'(p)\right)$ uniformly on every closed subinterval of $(0, 1)$, by the continuity of H and the uniform convergence $\left(V_{n_k}, V'_{n_k}\right) \to (V, V')$ on closed subintervals of $(0, 1)$.

Step 2. Uniqueness. Suppose V and U are two bounded solutions. Assuming that $U(p) > V(p)$ for some $p \in (0, 1)$, let $p_0 \in (0, 1)$ be the point where the difference $U - V$ is maximized. Thus we have $U(p_0) - V(p_0) > 0$ and $U'(p_0) - V'(p_0) = 0$. But then, the difference $U(p) - V(p)$ must be strictly increasing for $p > p_0$, a contradiction. (why? Suppose that $U(p_0) \leq V(p_0)$ and $U'(p_0) \leq V'(p_0)$. If $U'(p) \leq V'(p)$ for all $p > p_0$ then we must also have $U(p) < V(p)$ on that range. Otherwise, let

$$p_1 \triangleq \inf \left\{p \in [p_0, 1) : U'(p) > V'(p)\right\}$$

then $U'(p_1) = V'(p_1)$ by continuity, and $U(p_1) < V(p_1)$ since $U(p_0) \leq V(p_0)$ and $U'(p) < V'(p)$ on $[p_0, p_1)$. By the optimality equation, it follows that $U''(p_1) - V''(p_1) < 0$, therefore $U'(p_1 - \varepsilon) > V'(p_1 - \varepsilon)$ for sufficiently small $\varepsilon > 0$, and this contradicts the definition of p_1)

Step 3. Monotonicity. We want to show that the strategic specialist's equilibrium payoff is weakly increasing in the investors' prior belief ϕ. Suppose V is not weakly increasing on $[0, 1]$. Take a maximal subinterval $[p_0, p_1]$ on which V is strictly decreasing. Recall that $V(0) = 0$ and $V(1) = \frac{1+f(1-\gamma)}{r}$, then since $V(0) < V(1)$ it follows that $[p_0, p_1] \neq [0, 1]$. Take $p_1 < 1$. Since p_1 is a local minimum, $V'(p_1) = 0$. Also, $V(p_1) \geq \pi_{|p_1}(a^*, k^*)$ otherwise $V''(p_1) < 0$. Then

$$V(p_0) > V(p_1) \geq \pi_{|p_1}(a^*, k^*) \geq \pi_{|p=0}(a^*, k^*) = V(0)$$

then $p_0 > 0$. Therefore $V'(p_0) = 0$ and $V''(p_0) > 0$ (because $\pi_{|p_1}(a^*, k^*) \geq \pi_{|p_0}(a^*, k^*)$), and so p_0 is a strict local minimum, a contradiction.

Lemma 30 *The strategic specialist's value function is decreasing in the volatility σ, in the discount rate $r/$ and in the conflict of interest b.*

We can show below that the specialist's payoff is decreasing in the volatility σ, the proof for the comparative static with respect to r and b follows the same steps.

First, we can reformulate the Hamilton–Jacobi–Bellman equation as

$$V'' = G(p, V, V')$$

with boundary conditions $V(0) = 0$ and $V(1) = \frac{1+f(1-\gamma)}{r}$.

Then, the function $V_L (V_H)$ is called a subsolution (supersolution) of the restated problem if $V_L'' \geq G(p, V_L, V_L')$ $(V_H'' \leq G(p, V_H, V_H'))$. One of the properties of the sub and supersolution is that

$$V_L(p) \leq V(p) \leq V_H(p).$$

Let assume that $\sigma_2 > \sigma_1$ and suppose by contradiction that for some p, $V_{\sigma_2}(p) > V_{\sigma_1}(p)$. Then $V_{\sigma_2}(p) - V_{\sigma_1}(p)$ must attain a local maximum. At the maximum point we then have

$$V_{\sigma_2}''(p) - V_{\sigma_1}''(p) \leq 0.$$

Hence, the formulation of the HJB equation implies

$$G\left(p, V_{\sigma_1}, V'_{\sigma_1}\right) \geq G\left(p, V_{\sigma_2}, V'_{\sigma_2}\right),$$

which contradicts the assumption that $\sigma_2 > \sigma_1$ and $V_{\sigma_2}(p) > V_{\sigma_1}(p)$. Then, the specialist's value function is descresing in the volatility of the returns dR_t.

3.7 Appendix - B

Proof of Lemma 1

We could derive the stochastic evolution of investors' beliefs in two different ways. The first involve applying Girsanov's theorem and is the one used by Faingold and Sannikov (2011), while the second one follows directly from Bayes' rule and is adapted from Bolton and Harris (1999). I am going to follow the second approach, which allows for off-equilibrium beliefs, and can be directly employed to derive the Bellman equation for the specialist.

Proof. Consider the random change in belief from p_t over $[t, t + dt]$. Let dR_t be the signal change observed by the investors over this time interval. By Bayes' rule we have:

$$dp_t \equiv p_{t+dt} - p_t = \frac{p_t\left(1 - p_t\right)\left(f_B\left(dR\right) - f_S\left(dR\right)\right)}{p_t f_B\left(dR\right) + \left(1 - p_t\right) f_S\left(dR\right)} \tag{3.7}$$

If the actual action is a, while the investor expects $\hat{a}(p)$, then the probability density $f_S(dR)$ of increment dR is a normal random variable with mean $\hat{a}(p) dt$ and variance $\sigma^2 dt$. We exploit the second order Taylor series approximation $e^z \approx 1 + z + z^2/2$:

$$f_S\left(dR\right) \propto e^{-(dR-\hat{a}dt)^2/2\sigma^2 dt} = e^{\left(\hat{a}dR - \hat{a}^2 dt/2\right)/\sigma^2} \approx 1 + (\hat{a}dR - \frac{\hat{a}^2}{2}dt)/\sigma^2 + \frac{1}{2}(\hat{a}dR - \frac{\hat{a}^2}{2}dt)^2/\sigma^4$$

The realized signal dR depends on the actual action a taken by the specialist: $dR = adt + \sigma dZ$. Substituting this and cancelling all terms above order dt, we find:

$$f_S\left(adt + \sigma dZ\right) \approx 1 + \hat{a}\left(adt + \sigma dZ\right)/\sigma^2$$

Now we can substitute back into equation (3.7) to get:

$$dp \approx \frac{p(1-p)(\widetilde{a} - \hat{a})(adt + \sigma dZ)/\sigma^2}{1 + \bar{a}(p)(adt + \sigma dZ)/\sigma^2}$$

$$\approx p(1-p)(\widetilde{a} - \hat{a})(adt + \sigma dZ)/\sigma^2 \left[1 - \bar{a}(p)(adt + \sigma dZ)/\sigma^2\right]$$

$$\approx \left[p(1-p)(\widetilde{a} - \hat{a})(a - \bar{a}(p))/\sigma^2\right] dt + \left[p(1-p)(\widetilde{a} - \hat{a})/\sigma\right] dZ$$

Then, we obtain the equation in the statement of the proposition. ∎

Proof of Lemma 2

Proof. First, notice that the specialist has private information about his type θ. Then, we first need to derive the stochastic evolution of beliefs from the specialist's point of view. We can rewrite the Brownian motion Z^p as follows

$$\sigma dZ^p = dR_t - (p\widetilde{a} + (1-p)\hat{a})\,dt$$

$$= dR_t - adt - p(\widetilde{a} - \hat{a})\,dt$$

$$= dZ^S - p(\widetilde{a} - \hat{a})\,dt$$

Substituting in (3.2) we get

$$dp = \left[\frac{\chi(\widetilde{a}, \hat{a}, p)(a - \bar{a}(p))}{\sigma} - \frac{|\chi(\widetilde{a}, \hat{a}, p)|^2}{(1-p)}\right] dt + \chi(\widetilde{a}, \hat{a}, p)\,dZ^s$$

Notice that conditional on the specialist being the strategic type, the posterior on the behavioral type must be a supermartingale, because the specialist expects the beliefs about the behavioral type to decrease over time.

We can now derive the value function. From the Principle of Optimality, we know that $V(p)$ satisfies

$$V(p) = \max_{a \in [0,1]} \left\{ r\left(k\left(\gamma(a - f) + f\right) - abk\right) dt + e^{-rdt}\mathbb{E}_p\left[V(p + dp)\right]\right\}$$

where

$$\mathbb{E}_p\left[V(p + dp)\right] = V(p) + V'(p)\,\mathbb{E}_p\left[dp\right] + \frac{1}{2}V''(p)\,\mathbb{E}_p\left[dp\right]^2$$

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follows from Ito's Lemma. Substituting in the expression for the evolution of beliefs dp we find

$$\mathbb{E}_p\left[V\left(p+dp\right)\right] = V\left(p\right) + V'\left(p\right)\left[\frac{\chi\left(\widetilde{a},\hat{a},p\right)\left(a-\bar{a}\left(p\right)\right)}{\sigma} - \frac{\left|\chi\left(\widetilde{a},\hat{a},p\right)\right|^2}{\left(1-p\right)}\right]dt + V''\left(p\right)\frac{\left|\chi\left(\widetilde{a},\hat{a},p\right)\right|^2}{2}dt$$

Finally, using the approximation $e^{-rdt} = 1 - rdt$ we get

$$V\left(p\right) = \max_{a\in[0,1]}\left\{ \begin{array}{c} \left(k\left(\gamma\left(a-f\right)+f\right)-abk\right)dt \\ + \left(1-rdt\right)\left[V\left(p\right)+V'\left(p\right)\left[\frac{\chi(\widetilde{a},\hat{a},p)(a-\bar{a}(p))}{\sigma}-\frac{|\chi(\widetilde{a},\hat{a},p)|^2}{(1-p)}\right]dt + V''\left(p\right)\frac{|\chi(\widetilde{a},\hat{a},p)|^2}{2}dt\right] \end{array}\right\}$$

rearranging and eliminating terms of order $(dt)^2$, we get the expression for the value function displayed in the proposition. ∎

Proof of Theorem 1

Proof. Let us start by showing that $(a^*, k^*) = (0, 0)$ cannot be an equilibrium for every p. If $\hat{a} = 0$ and $p < \bar{p}$ then the best response is to set $k = 0$, but if $k = 0$ the FOC for the specialist becomes $\frac{p(1-p)V'(p)}{r\sigma^2} > 0$ which means that the specialist has an incentive to increase his effort a^*, which is a contradiction.

Similarly, $(a^*, k^*) = (1, 1)$ is not an equilibrium for any p. Suppose that $\hat{a} = 1$, then $k = 1$, however the FOC for the specialist becomes $(\gamma - b) < 0$ which means that the specialist has an incentive to decrease his optimal choice a^*, which is a contradiction.

It is straightforward to see that $(a^*, k^*) = (1, 0)$ cannot be an equilibrium either, because if $\hat{a} = 1$ the investors' best response is to set $k = 1$.

Now we can find the threshold for the specialist's reputation that identify the exploitation region. Suppose that $\hat{a} = 0$. The investor's best response is $k = 1$ if and only if $p > \bar{p}$, where $\bar{p}$ is defined as $(1 - \gamma)(\widetilde{p}\widetilde{a} - f) - f - s = 0$. For $p < \bar{p}$, we have $k^* = 0$.

For reputation values $p \in (\underline{p}, \bar{p})$, the first order conditions hold with equality. The investor's FOC defines the specialist's effort choice, while the specialist's FOC defines the optimal investment, as function of p.

We can now find the interval of p supporting $(0, 0)$ as an equilibrium. The lower threshold $\underline{p}$ is defined by the following

$$V\left(\underline{p}\right) = c \tag{3.8}$$

We know that $V(0) = 0 < c$, which means that given the monotonicity of the specialist's value

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function $\underline{p} > 0$. In order to make sure that $\underline{p} < 1$ we need to impose the following parametric restriction:

$$V(1) = \frac{1 + f(1 - \gamma)}{r} > c$$

that is, the payoff that the specialist can capture when his maximum reputation is achieved needs to be higher than the cost of running the fund c. Otherwise, the specialist would never participate to this market. ∎

Proof of Property 1

Proof. Given the closed form solution for the effort choice given by:

$$a^* = \frac{f + s + f(1 - \gamma)}{(1 - \gamma)(1 - p)} - \frac{p}{(1 - p)}\widetilde{a},$$

we can just differentiating it to immediately obtain

$$\frac{da}{df} > 0, \frac{da}{ds} > 0$$

and

$$\frac{da}{d\gamma} = \frac{(f + s)(1 - p)}{(1 - \gamma)^2 (1 - p)^2} > 0$$

We can then apply Cramer's rule to the set of FOCs to show that the optimal effort choice is decreasing in the reputation value p :

$$\frac{da}{dp} = \frac{\begin{vmatrix} u_{kk} & -u_{kp} \\ \pi_{ak} & -\pi_{ap} \end{vmatrix}}{\begin{vmatrix} u_{kk} & u_{ka} \\ \pi_{ak} & \pi_{aa} \end{vmatrix}} = \frac{(1 - \gamma)(\widetilde{a} - \hat{a})(\gamma - b)}{(b - \gamma)(1 - \gamma)(1 - p)} < 0$$

∎

Proof of Property 2

Proof. The threshold $\underline{p}$ is given by the condition (3.8). Since the left hand side is increasing in p, an increase in c leads to an increase in the threshold $\underline{p}$. Moreover, we have shown in Appendix A that the specialist's value function is decreasing in σ, which means that an increase in the value of the threshold $\underline{p}$ is needed in order to keep satisfying condition (3.8). ∎

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