Market Turmoil and Destabilizing Speculation

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Abstract

This paper explores how speculators can destabilize financial markets by amplifying negative shocks in periods of market turmoil, and confirms 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 search 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.

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1 Introduction

Uncertainty has dominated financial markets of late. The most recent example is the sovereign debt crisis in Europe, but 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. 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 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

[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.

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 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.

Moreover, there exists a price at which the *market freezes*. Intuitively, this is the price that makes speculators indifferent between selling and holding the asset. Hence, in my model the market can freeze even in the absence of asymmetric information. In other words, an uncertainty shock may not only amplify negative shocks and destabilize financial markets, but also dry up liquidity completely, especially when uncertainty is persistent. 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 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 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 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 presents the baseline model and Section 3 characterizes the two equilibria that can arise and the resulting price paths. Section 3.3 analyzes the impact of trading frictions, market liquidity and the persistence of uncertainty on equilibrium behavior. Section 3.4 presents my uniqueness result and the result on market fragility. Section 5 gives evidence for the main mechanism hypothesized and Section 6 weighs the different motivations underlying funds' strategies. Finally, Section 7 discusses the findings and concludes. The appendix 8 contains the proofs. The theoretical Supplementary Appendix extends the model to study the effect of the introduction of a transaction cost such as a Tobin tax, while the empirical Supplementary Appendix provides further insights on funds' trading behavior during the European debt crisis by exploiting cross-sectional variation across funds.

1.1 Related Literature

To my knowledge, this paper is the first to show that, even when assets' fundamentals remain constant, uncertainty about future market shocks in conjunction with trading frictions lead speculators to aggravate the effects of market shocks by liquidating their holdings.

This paper 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 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

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

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

speculators' responses to an increase in uncertainty. Interestingly, in my model trading might come to a complete halt even in absence of any information asymmetry about the asset's value.

The most closely related paper to this is Diamond and Rajan (2011), which shows that to profit from the future fire sale a bank's management might refrain from selling illiquid assets, even though such sales could save the bank. As in my paper, this behavior stems not from uncertain fundamental values but from the potentially low future fire sale prices at which illiquid assets will have to be sold. In my model, however, the strategic interaction among speculators in a market with trading frictions, rather than a risk-shifting motive, drive the dynamics of the asset price.

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. (2011)), 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 estimating the impact of speculators' behavior on issuers' balance sheets in Section 5, showing that issuers are forced to borrow at higher rates and shorter maturities.[5]

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.[6] 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 of the same type as in Duffie et al. (2007).[7] 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. This overshooting of the price is related to the occurrence of predatory trading as shown by Brunnermeier and Pedersen (2005). The main difference is that, in this paper, the key ingredient is the interaction among speculators which give rise to two different equilibria, one stabilizing and one destabilizing,

[5] 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.

[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] 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.

and potentially to market freeze. Moreover, when the severity of the future shock changes over time, this paper also generates endogenous volatility, i.e. the effects of uncertainty in heightening price volatility are amplified by the behavior of speculators in distressed markets.[8]

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. Long-term investors provide a downward-sloping demand curve to other market participants, while speculators 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; while the long-term investors can be interpreted as market makers or uninformed investors. 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 given time, a speculator holds either 0 or 1 unit of the asset does not undermine generality.

[8] Two additional amplification mechanisms have been shown to be important. Kiyotaki and Moore (1997) have highlighted agents' balance sheets as a source of amplification, while Routledge and Zin (2009), Caballero and Krishnamurthy (2008), and Easley and O'Hara (2010) show that investors' Knightian uncertainty about asset values might cause them to disengage from markets and in this way amplify the crisis. The mechanism posited here complements these papers by specifying why and how markets become more fragile when uncertainty spikes, without the need to rely on collateral constraints or specific assumption about preferences.

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

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, who form the competitive fringe. The primary difference between these investors and speculators is that the long-term investors are more likely to trade according to fundamentals and to employ less aggressive trading strategies. 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. These long-term investors can be thought of like mutual funds, pension funds or market makers.

The trading mechanism works as follows. The market clearing price $p(t)$ solves $D(p_t) + x(t) = S(t)$, where $D(p_t)$ captures the long-term investors' holdings and $x(t)$ is the fraction of speculators holding the asset at time t. The asset is traded at the price

$$p(t) = \frac{\delta}{r} - \lambda\left(S(t) - x(t)\right). \tag{1}$$

The first term in (1) is the fundamental value $\frac{\delta}{r}$: the net present value of profits to investors when they hold the assets forever and collect the entire future cash flow.[14] The parameter λ measures the

[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, I 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 the supplementary appendix, I investigate the introduction of small trading costs, such as a "Tobin tax" on financial transactions.

[14] Xiong (2001), Kyle and Xiong (2001) and Brunnermeier and Pedersen (2005), among others, employ a similar

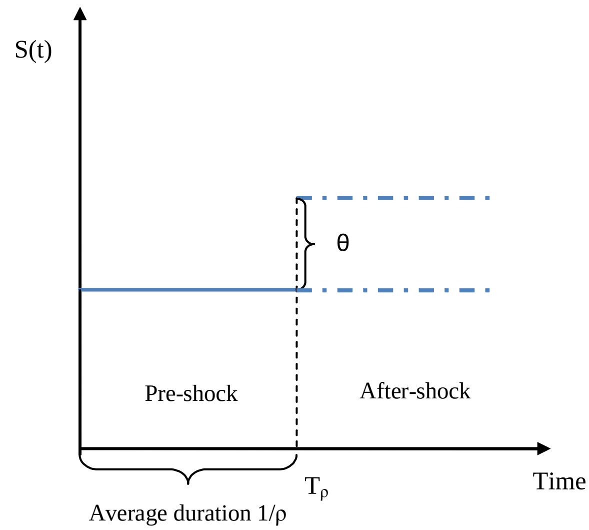


Figure 1: Asset supply might jump at random time T_ρ due to a negative shock.

permanent liquidity effects of trading, and a larger λ captures lower liquidity by long-term investors. As $x(t)$ increases, the price at which the long-term investors can access the asset increases. Grossman and Miller (1988) shows that a 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). Hence, asymmetric information and ownership structure should be among the major determinants of λ, because for an asset with more asymmetric information or more concentrated ownership, the price will more strongly adjust when the net supply of the asset changes.[15]

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). 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).

*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 sometime in the future. I assume that at random time T_ρ, distributed according to a

formulation for the pricing relationship.

[15] In Section 5 I shall show that assets held by fewer money market funds (high-λ assets) are indeed more likely to be subject to the mechanism suggested by the model.

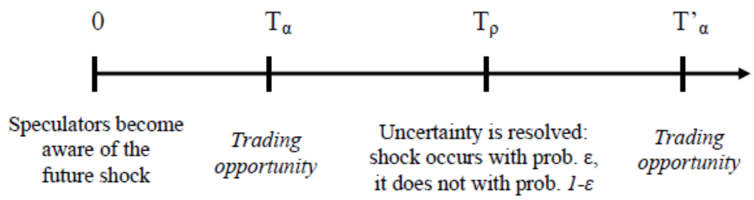


Figure 2: The timeline.

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.[16] 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 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).

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 outflows create price pressure in the securities held in common by distressed funds because they tend to liquidate their positions. 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, and Adrian and Shin (2010) find empirical support for this liquidity spiral in data on investment banks. 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.

Figure 2 shows the timeline of the model. At time $t = 0$ the speculators become aware that the asset price might be depressed by the realization of the shock at time T_ρ. They can trade the asset before and after the realization of the shock at the random times T_α and/or T'_α.

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

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.

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.[17]

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

$$V(a,t) = \mathbb{E}_t[\int_t^{T_\alpha} e^{-r(s-t)}\delta a ds + e^{-r(T_\alpha - t)}\{V(a(T_\alpha), T_\alpha) - p(T_\alpha)[a(T_\alpha) - a]\}], \tag{2}$$

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*

$$u_a = \frac{\delta}{r+\alpha} > q(t), \tag{3}$$

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

[17] 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.

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

$$\mathbb{E}\left[\int_t^{T_\alpha} e^{-r(s-t)}\delta a^U ds - \left(p(t) - e^{-r(T_\alpha - t)}p(T_\alpha)\right)a^U\right], \tag{4}$$

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 (4) and expression (3) 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*

$$u_a^U = \frac{\delta}{r + \alpha + \rho} > q^U(t), \tag{5}$$

where

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

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 1 (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 1 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 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 1 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 1 (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 which 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.

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 1 *An equilibrium is a time-path* $\left(\left\{a^U(t)\right\}, \{a(t)\}, \{p(t)\}\right)$ *that satisfies (3), (5) and market clearing (1) given initial conditions* $p(0)$ *and* $x(0)$*. 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 unique equilibrium in Section 6 by positing that the speculators' perceptions of the severity of the crisis θ fluctuate over time. As we can see in Proposition 3, 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

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

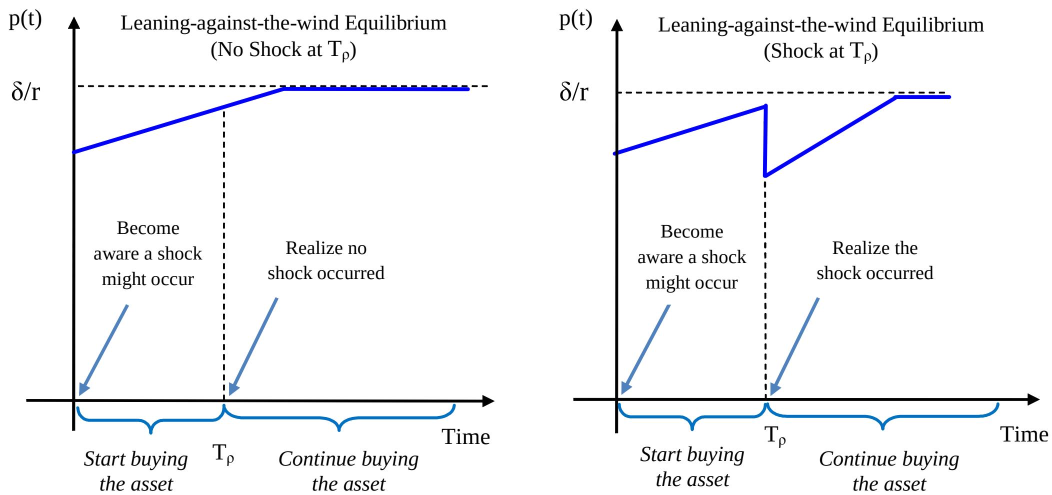


Figure 3: The price path in a "*leaning-against-the-wind*" equilibrium where the shock does not occur (left panel) and where it does (right panel) at random time T_ρ.

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 3 (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 3 shows that in the first type of equilibrium the price rises over both intervals $[0, T_\rho)$ 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 2 (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 $\underline{\theta}(p(t)) < \bar{\theta}(p(t))$.

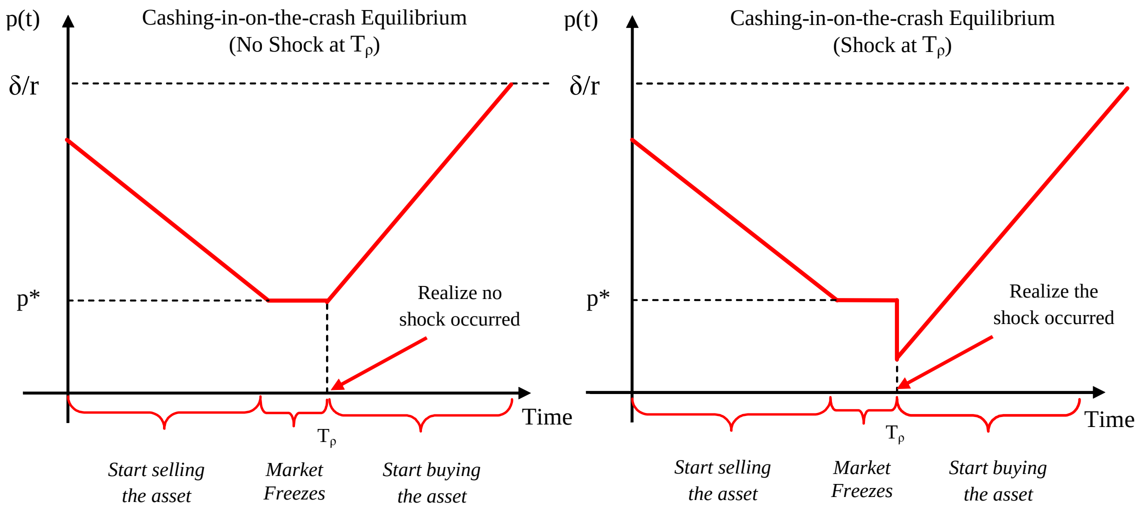


Figure 4: The price path when a "*cash-in-on-the-crash*" equilibrium emerges and the shock does not occur at random time T_ρ (left panel) and when it does occur (right panel). The flat line in the right panel captures the market freeze when the price reaches the value of p^*.

Proposition 2 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 $\theta \in \left[\underline{\theta}(p(t)), \bar{\theta}(p(t))\right]$, 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 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 $(p(t) < \frac{\delta}{r})$, 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 $\underline{\theta}(p(t))$ and $\bar{\theta}(p(t))$ 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 3 (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 3 is represented in Figure 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 3 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 negative shocks and destabilize financial markets, but also dry up liquidity completely. As the right panel in Figure 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.

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).

The evaporation of liquidity in the market-freeze phase of the equilibrium is a consequence of the coordinated trading behavior of the speculators highlighted in Proposition 2. The sudden evaporation of liquidity was observed in many sectors of financial markets in 2007-09. Gorton and Metrick (2009) proposes the explanation 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. This also leads to a sudden increase in the returns to liquidity-provision, which follows from the fact that the fundamental value of the asset is unaffected while its price is driven down by speculation. Nagel (2011) provides evidence consistent with this prediction, finding that during the recent crisis, the returns to liquidity-provision increased significantly and were closely correlated with the VIX index.

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. 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.

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:

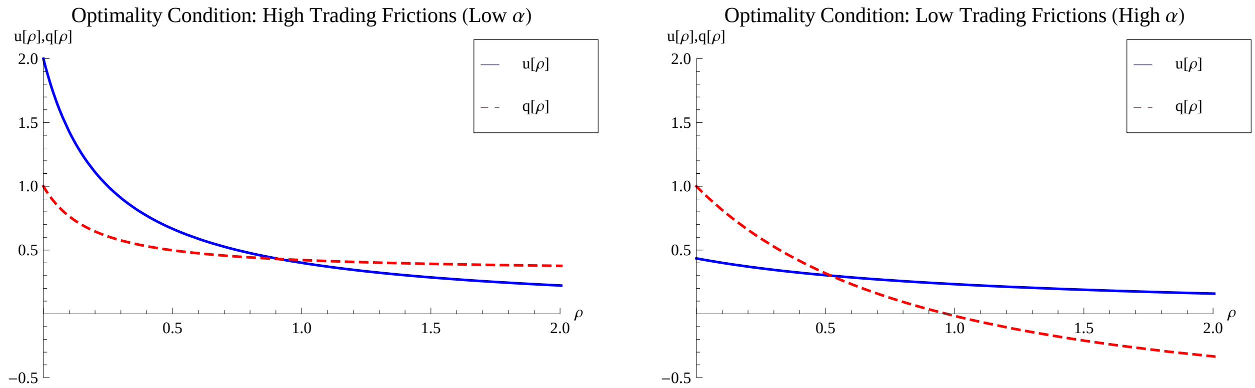
Proposition 4 (Trading Frictions and Price Fluctuations) *In a cashing-in-on-the-crash equilibrium less trading friction, i.e. higher α, leads to a greater decline in the asset price for $t < T_\rho$ and a faster recovery towards the fundamental value for $t \geq T_\rho$.*

The previous proposition follows from Lemma 3 and Proposition 3. 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.

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



(a) (b)

Figure 5: The effect on speculators' incentives of the persistence of uncertainty ρ for low and high value of the trading frictions α.

into the effect of trading frictions and uncertainty on the speculators' incentives, ultimately reaching the following result:

Proposition 5 (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' 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 $t < T_\rho$. Suggestive empirical evidence consistent with this result 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. They find that the investors who expect liquidity shocks retain liquid assets and sell those that have relatively high temporary price impact.

The intuition for the other results in the previous proposition can be better understood by analyzing Figures 5 and 6. Figure 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.

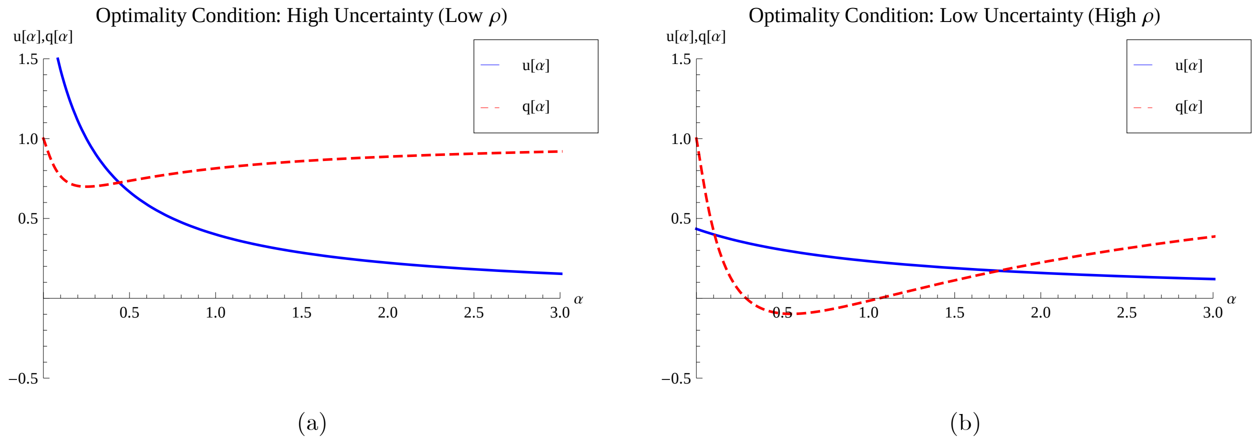


Figure 6: The effect of trading frictions α on speculators' incentives for low and high values of the persistence of uncertainty ρ.

To illustrate the second part of proposition 5, Figure 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.

3.4 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[18]

$$\frac{d\theta_t}{\theta_t} = \mu dt + \sigma dW, \tag{6}$$

where μ and σ are constants.[19] 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 ($\mu < 0$) 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

[18] 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.

[19] 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).

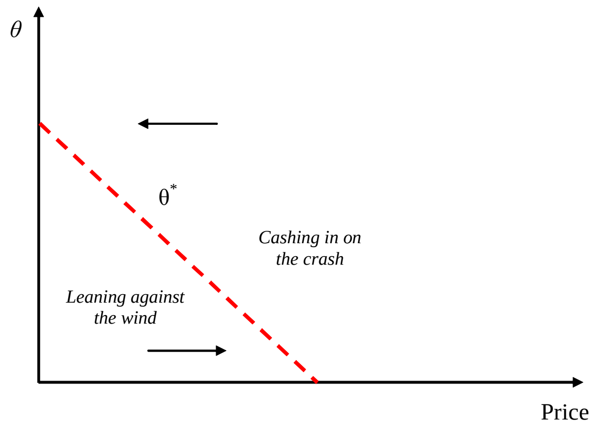


Figure 7: The unique equilibrium

unique equilibrium. In fact, it triggers a contagion argument that leads to equilibrium uniqueness as shown by the next proposition.

Proposition 6 (Unique Equilibrium) *When the severity of the shock θ follows (6) 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 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 7 has three main properties.

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.

Property 2 shows that the equilibrium also has implications for the price path. The arrows in Figure 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. In other words, amplification of market shock is more likely when the market has just gone through a bout of euphoria, driving prices up, which resembles the mechanism proposed by Brunnermeier et al. (2008) in the analysis of carry trades in exchange markets. 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.

4 Discussion

In this section, I discuss the main simplifying assumptions of the model.

Multiple shocks. In the model we have considered the case of a single potential shock. This is clearly an important simplification, as uncertainty may not be suddenly resolved after the random time T_ρ. However, the model could accommodate multiple shocks with exponentially distributed arrival rate. The main difference would be that with multiple shocks the speculators have a greater incentive to sell and wait to repurchase until the last shock, as the price will continue to fall due to multiple shocks. In other words, in the *cashing-in-on-the-crash* equilibrium the recovery phase will start only when the speculators expect no more shocks to occur.

Fundamental shocks. To highlight the speculators' strategic motive, I have focused on shocks that do not affect the cash flow or fundamental value of the asset δ.[20] This allows me to show that the amplification of market shocks does not necessarily depend on the speculators' precautionary motive but can be the result of their desire to profit from the shocks. The model can be extended to allow for a fundamental shock, for instance, by assuming that at some random time in the future the cash flow of the asset, δ, may decrease to a lower value $\underline{\delta}$. Interestingly, while the speculators would have a greater incentive to sell in anticipation of this shock, as now they fear the decline in value, they would not buy it back again if a sufficiently severe shock occurs, i.e. $\underline{\delta} = 0$. In the case of a small shock, i.e. $\delta > \underline{\delta} > 0$, instead, the price after the shock would converge to a different fundamental value $\underline{\delta}/r$. Hence, the empirical predictions of this model are different from those of a model in which the asset's value is affected, which means that the different mechanisms can be empirically disentangled.

Heterogeneous valuation. To simplify the analysis, it is assumed that the only sources of heterogeneity among speculators are the time at which they are able to trade and, as in Section 3.4, the information they possess when they trade. However, we could assume that speculators value the asset differently, for instance, because they have different hedging motives. The main qualitative result of the paper would still hold, namely that speculators would still find it optimal to react to an expected price fall by selling their holdings; the difference is that there would not exist a unique price p^* at which the trading comes to a complete halt, because if speculators have heterogeneous valuations, there is no unique price at which all are indifferent between selling and buying.

Long-term investors. 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. Vayanos and Woolley (2013) offer a model that explains 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 that are 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 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)). In my model the long-term investors can also capture uninformed market-makers as in the tradition of Glosten and Milgrom (1985).

State-contingent λ. In the model the price impact is assumed to be constant, in the spirit of

[20] In the asset pricing literature an increase in uncertainty is usually captured by time-varying second moments of dividend or consumption growth (see for instance, Veronesi (1999), Bansal and Yaron (2004) and Bloom (2009) or, recently, on uncertainty about the impact of government interventions Pastor and Veronesi (2011b)). In my model, instead, the fundamental value of the asset does not change, but its price may be severely affected by jumps in supply. This way of modeling uncertainty is not intended to capture uncertainty about the fundamental value, but uncertainty about market conditions, namely the price at which the asset can be traded.

Kyle (1985). However, it is plausible that market liquidity might change after T_ρ depending on the realization of the shock. For instance, λ could be higher if the shock is realized than if it is not. This might capture situations in which long-term investors are less willing to provide liquidity to other market participants after a fire sale, for instance, because they fear subsequent shocks. If the price impact λ is greater after time T_ρ when the shock is realized, then the only difference from the current framework is that the price would converge to the fundamental value after T_ρ more rapidly, since speculators would have a greater price impact in the recovery phase.

5 Empirical Analysis

5.1 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."[21]

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. Moreover, several features of the money market funds match the theoretical framework developed in the previous sections. First, due to strict regulatory constraints, money market funds can only trade safe (i.e. highly rated and liquid) securities, which makes the assumption that the fundamental value of the assets δ is constant more likely to hold. Second, funds mainly trade commercial paper and asset-backed commercial paper in over-the-counter markets, where trading frictions are significant. Third, funds do not trade directly among themselves but they interact with market-makers and dealers, which might be thought of like the long-term investors in my model. Finally, the mechanism I propose does not require the use

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

of leverage or the existence of borrowing constraints, as in other complementary mechanisms (e.g. Kiyotaki and Moore (1997)), and money market funds are not leveraged institutions.

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, in the supplementary appendix 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 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.

5.2 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 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 in 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 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 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.[22] 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 2 and the time-series pattern described in Figure 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 of complementarity, such as unobserved heterogeneity in risk. Section 6 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:

[22] Afonso et al. (2013) show that the majority of banks in the interbank market form long-term, stable lending relationships, which have a significant impact on how liquidity shocks are transmitted across the market.

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 the Supplementary Appendix 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 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 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 and is discussed in the Supplementary Appendix.

5.3 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 (2013) 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.

5.4 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 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.

5.5 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. Moreover, this measure is very persistent over time with a correlation around 0.7, which shows that the majority of banks form long-term, stable lending relationships with money market funds, which have a significant impact on how funds behave when uncertainty spikes.

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[23]

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \varepsilon_{i,t}, \tag{7}$$

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 (7) over 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 (7) 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.[24] 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 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

[23] I have estimated the same regression model (7) 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.

[24] 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.

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 2 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-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 4 shows the estimated coefficients of the following regression model for the two samples:

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\,Ties_{g,\ Aug\ 11} \times Post + \alpha_1 Issuer\,CDS_{g,t} + \alpha_2 Issuer\,CDS_{g,t} \times Post + \varepsilon_{i,t} \tag{8}$$

which is the same as in (7) 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.

As I show in the Supplementary Appendix, the funds that are more likely to behave as predicted by the model are institutional funds and funds that tend to invest in riskier asset classes (e.g. foreign bank obligations and ABCP). This evidence contradicts the hypothesis that a precautionary motive leads the more risk-averse funds to reduce their exposure to issuers with fewer funding relationships.

5.6 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 10 and 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 5 shows the results of the following regression model:

$$Issuer\ Maturity_{g,t} = \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \gamma_t + \phi_g + \varepsilon_{g,t}, \tag{9}$$

where the dependent variable is the average maturity of the assets sold by issuer g at time t. As in the previous regression model (7), 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 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 12 depicts the time-series coefficients of the following regressions:

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

where $\mathbf{1}_{(\tau=t)}$ 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 (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 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 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 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.

6 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.

6.1 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 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 3 and 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 (7)

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g,\ Aug\ 11} \times Post + \alpha_1 Break\ the\ Buck_{i,t} + \alpha_2 Break\ the\ Buck_{i,t} \times Post + \varepsilon_{i,t}, \tag{10}$$

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 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 (7) and exclude the funds with a NAV below 1, approximately 20% of my sample. Column (2) of Table 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 (10) 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.

6.2 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."[25]

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 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 threefold. First, I estimate (8) 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 8 show the results for the funds with low exposure, Columns (3) and (4) those for the funds

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

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 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 intervention 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.

6.3 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.[26] 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 char-

[26] 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.

acteristic 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 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.

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.

7 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. 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 dynamics of housing prices. Recent papers by Haughwout et al. (2011) and Bayer et al. (2011) identify real-estate investors as a key factor in the house price surge and crash. 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, and they 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. 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.

8 Appendix A – Proofs

Proof of Lemma 1.

I can rewrite the value function (2) as

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

then subtracting $p(t)a$ 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

$$\max_{a' \geq 0} \int_t^{T_\alpha} e^{-r(s-t)}\delta a' ds - \left\{p(t) - \mathbb{E}\left[e^{-r(T_\alpha - t)}p(T_\alpha)\right]\right\}a'. \tag{11}$$

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 (11) as

$$u(a) = \mathbb{E}\left[\int_0^{T_\alpha - t} e^{-rs}\delta a ds\right] = a\frac{\delta}{r+\alpha}, \tag{12}$$

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

$$\mathbb{E}\left[e^{-r(T_\alpha - t)}p(T_\alpha)\right] = \alpha \int_0^\infty e^{-(r+\alpha)s}p(t+s)\,ds. \tag{13}$$

Substitute (12) and (13) into (11) 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

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

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. ■

Proof of Proposition 1.

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

$$\begin{aligned}
\frac{\delta}{r+\alpha+\rho} &= [p^U(t) - \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}(e^{-\rho(\tau_\alpha - t)} p^U(\tau_\alpha) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} p(\tau_\alpha|\tau_\rho)\, d\tau_\rho) d\tau_\alpha] \qquad (14)\\
&= [p^U(t) - \left\{ \begin{array}{c} \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}(e^{-\rho(\tau_\alpha - t)} p^U(t) \\ + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} (\varepsilon(F - \lambda(S+\theta^*)) + (1-\varepsilon)F)\, d\tau_\rho) d\tau_\alpha \end{array} \right\}] \\
&= [p^U(t) - \left\{ \begin{array}{c} \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}(e^{-\rho(\tau_\alpha - t)} p^U(t) \\ + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} (F - \varepsilon\lambda(S+\theta^*))\, d\tau_\rho) d\tau_\alpha \end{array} \right\}] \\
&= p^U(t) - \frac{\alpha p^U(t)}{r+\alpha+\rho} + \frac{\alpha(F - \varepsilon\lambda(S+\theta^*))}{r+\alpha+\rho} - \frac{\alpha(F - \varepsilon\lambda(S+\theta^*))}{r+\alpha} \\
&= \frac{p^U(t)(r+\rho)}{r+\alpha+\rho} - \alpha(F - \varepsilon\lambda(S+\theta^*)) \frac{\rho}{(r+\alpha+\rho)(r+\alpha)},
\end{aligned}$$

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 1.

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 (14) 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

$$\begin{aligned}
\frac{\partial \theta^*}{\partial \rho} &= \frac{\left[\alpha\left(\frac{\delta}{r} - \varepsilon\lambda S\right) - \left(\frac{\delta}{r} - \lambda S\right)(r+\alpha)\right]\varepsilon\lambda\alpha\rho - \varepsilon\lambda\alpha\left[\delta(r+\alpha) + \alpha\left(\frac{\delta}{r} - \varepsilon\lambda S\right)\rho - \left(\frac{\delta}{r} - \lambda S\right)(r+\rho)(r+\alpha)\right]}{(\varepsilon\lambda\alpha\rho)^2} \\
&= \frac{-\left(\frac{\delta}{r} - \lambda S\right)\rho - \delta + \left(\frac{\delta}{r} - \lambda S\right)(r+\rho)}{(\varepsilon\lambda\alpha\rho)^2} = \frac{-\lambda S r}{(\varepsilon\lambda\alpha\rho)^2} < 0
\end{aligned}$$

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

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

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

Proof of Lemma 3.

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) 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 3:

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

which is increasing over time. ■

Proof of Proposition 2.

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

$$\widetilde{p}(\tau_\alpha) = \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(e^{-\rho(\tau_\alpha - t)} p^c(\tau_\alpha) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho - t)} p(\tau_\alpha | \tau_\rho)\, d\tau_\rho\right) d\tau_\alpha. \tag{15}$$

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 (15); using Lemma 3 we can rewrite the first term as

$$\begin{aligned}
&\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}\left(e^{-\rho(\tau_\alpha - t)} p^c(\tau_\alpha)\right) d\tau_\alpha \qquad (16)\\
&= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)} p^c(\tau_\alpha)\, d\tau_\alpha\\
&= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)}\left(p^c(t)\, e^{-\alpha(\tau_\alpha - t)} + (F - \lambda S)\left(1 - e^{-\alpha(\tau_\alpha - t)}\right)\right) d\tau_\alpha\\
&= \alpha\left(\frac{p^c(t)}{r + 2\alpha + \rho} + \frac{\alpha(F - \lambda S)}{(r + \alpha + \rho)(r + 2\alpha + \rho)}\right).
\end{aligned}$$

The second term in (15) 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 (with weight ε) and of the price once the shock reveals to be temporary (with weight $(1-\varepsilon)$):

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

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 (15) as follows

$$
\begin{aligned}
&\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)}\left(\int_t^{\tau_\alpha}\rho e^{-\rho(\tau_\rho-t)}p(\tau_\alpha|\tau_\rho)\,d\tau_\rho\right)d\tau_\alpha \qquad (17)\\
&=\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)}\left(\int_t^{\tau_\alpha}\rho e^{-\rho(\tau_\rho-t)}\left[\begin{array}{c} p(t)\,e^{-\alpha(\tau_\alpha-t)}+\left(1-e^{-\alpha(\tau_\alpha-t)}\right)(F-\lambda S+\lambda)\\ -\varepsilon\lambda\theta\left(1-e^{-\alpha(\tau_\alpha-t)}\right)\end{array}\right]d\tau_\rho\right)d\tau_\alpha\\
&=\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)}\Big(p(t)\,e^{-\alpha(\tau_\alpha-t)}\left(1-e^{-\rho(\tau_\alpha-t)}\right)+\left(1-e^{-\rho(\tau_\alpha-t)}\right)\left(1-e^{-\alpha(\tau_\alpha-t)}\right)(F-\lambda S+\lambda)\\
&-\varepsilon\lambda\theta\left(1-e^{-\rho(\tau_\alpha-t)}\right)\left(1-e^{-\alpha(\tau_\alpha-t)}\right)\Big)d\tau_\alpha\\
&=\Big(\alpha p^c(t)\left(\frac{\rho}{(r+2\alpha)(r+2\alpha+\rho)}\right)+\alpha(F-\lambda S+\lambda)\left(\frac{\alpha}{(r+\alpha)(r+2\alpha)}-\frac{\alpha}{(r+2\alpha+\rho)(r+\alpha+\rho)}\right)\\
&-\alpha\varepsilon\lambda\theta\left(\frac{\alpha}{(r+\alpha)(r+2\alpha)}-\frac{\alpha}{(r+2\alpha+\rho)(r+\alpha+\rho)}\right)\Big).
\end{aligned}
$$

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

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

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

$$
\underline{\theta}(p(t))=\left[\frac{\delta}{r+\alpha+\rho}-p^c(t)\left(1-\left(\frac{\alpha\rho}{(r+2\alpha)(r+2\alpha+\rho)}\right)\right)-\alpha(F-\lambda S+\lambda)\mathbb{H}\right]\frac{1}{\alpha\varepsilon\lambda\mathbb{H}}. \qquad (18)
$$

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 (15) the different expected price path:

$$\int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha - t)}(e^{-\rho(\tau_\alpha - t)}p^c(\tau_\alpha))d\tau_\alpha \tag{19a}$$
$$= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)}p^c(\tau_\alpha)\,d\tau_\alpha$$
$$= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha - t)}\left(\lambda - (\lambda - p(t))\,e^{-\alpha(\tau_\alpha - t)} + (F - \lambda S)\left(1 - e^{-\alpha(\tau_\alpha - t)}\right)\right)d\tau_\alpha$$
$$= \frac{\alpha\lambda}{r+\alpha+\rho} - \frac{\alpha\lambda}{r+2\alpha+\rho} + \frac{\alpha p(t)}{r+2\alpha+\rho} + \frac{\alpha(F-\lambda S)}{r+\alpha+\rho} - \frac{\alpha(F-\lambda S)}{r+2\alpha+\rho}$$
$$= \alpha\lambda\left(\frac{\alpha}{(r+\alpha+\rho)(r+2\alpha+\rho)}\right) + \frac{\alpha p(t)}{r+2\alpha+\rho} + \alpha(F-\lambda S)\left(\frac{\alpha}{(r+\alpha+\rho)(r+2\alpha+\rho)}\right).$$

By substituting (19a) in the optimality condition identified in Lemma 2, I can find a different threshold for the severity of the shock:

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

This completes part (i).

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

$$\frac{\delta}{r+\alpha+\rho} > p^c(t) - \widetilde{p}(\tau_\alpha) \tag{20}$$

Comparing condition (16) with (19a) shows that the threshold $\overline{\theta}(p(t))$ that solves (20) 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 1: when speculators interact with each other in the market, the thresholds depend (negatively) on the price at time t, i.e. $\frac{\partial\overline{\theta}(p_t)}{\partial p_t} < 0$ and $\frac{\partial\underline{\theta}(p_t)}{\partial p_t} < 0$. ■

Proof of Proposition 3.

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.[27] 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.

[27] Notice that the condition on $x(0)$ can be relaxed if I allow the speculators to short-sell 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 1, 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 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 4.

This follows from Lemma 3 and the cashing-in-on-the-crash equilibrium of Proposition 2. 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 5.

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 5 and 6. The left hand side of the optimality condition in Lemma 2, $\frac{\delta}{r+\alpha+\rho}$ is decreasing in both α and ρ as depicted by the blue curves in the Figures 5 and 6.

The capital gain in 17, 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:

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

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

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

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 6.

Finally, I can investigate the effect of market depth λ. The effect on 17 is positive if $(1-S)-\varepsilon\theta > 0$, which is true for small enough probability of the shock ε. ■

Proof of Proposition 6.

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 2 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 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 $\underline{\theta}(p(t))$, 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 ($\theta < \underline{\theta}(p(t))$). 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. ■

9 Appendix B- Evidence of Strategic Motive

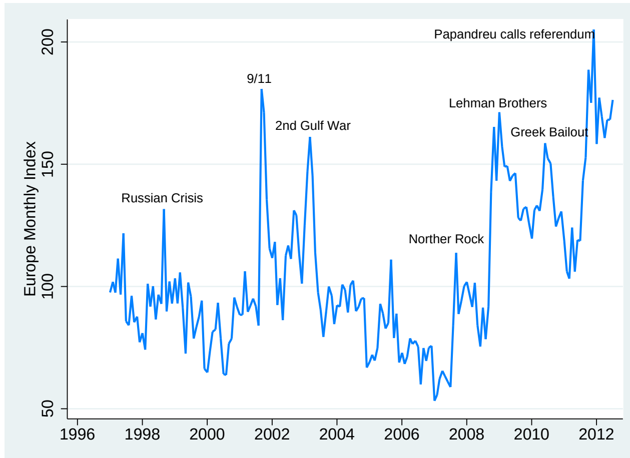


Figure 8: European Political Uncertainty Index.
Notes: The panel above plots the European Political Uncertainty index proposed by Baker et al. (2011) for the period 1997-2012. The index is constructed using two types of underlying components. One component quantifies newspaper coverage of policy-related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

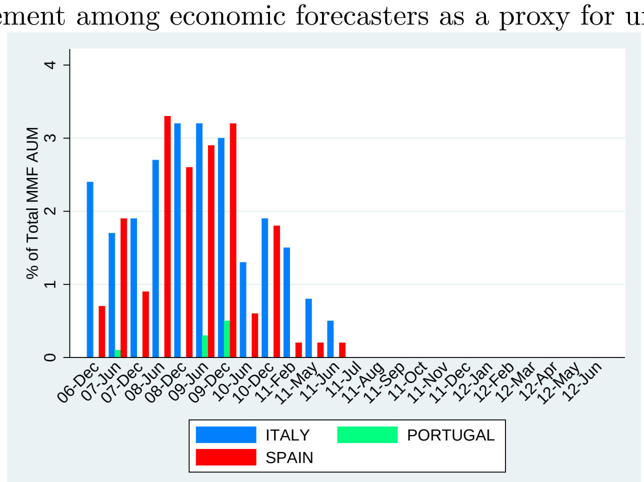


Figure 9: MMMFs exposure to the PIIGS.
Notes: The panel above plots MMFs exposure, measured as the fraction of assets under management, to Portugal, Italy and Spain for the period December 2006 to June 2012. MMFs had no exposure to Greece and Ireland starting in 2010 (Source: Fitch and ICI).

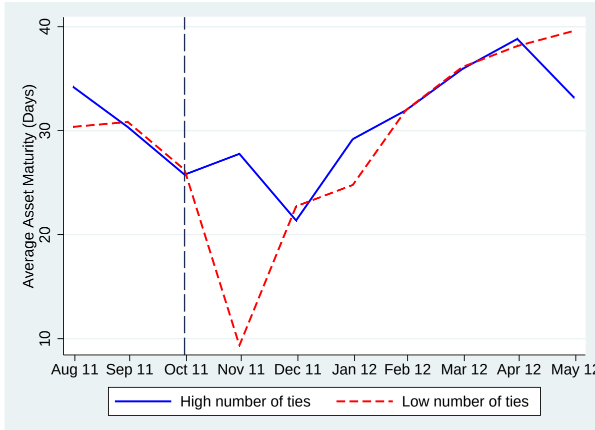


Figure 10: Average Asset Maturity
Notes: The panel above plots the average asset maturity issued by European institutions that have above (the blue continuous line) and below (the red dashed line) average number of borrowing relationships with MMFs for the period August 2011-May 2012. The vertical line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

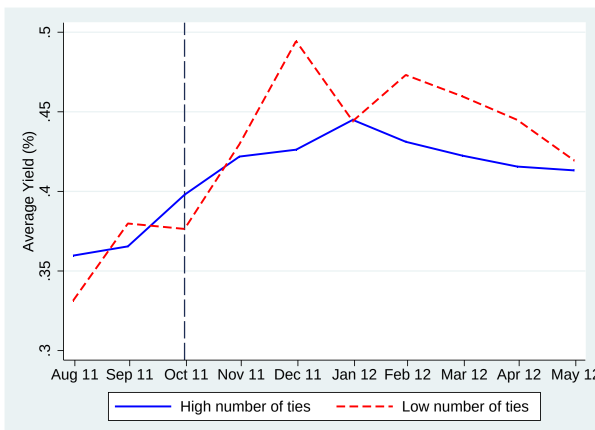
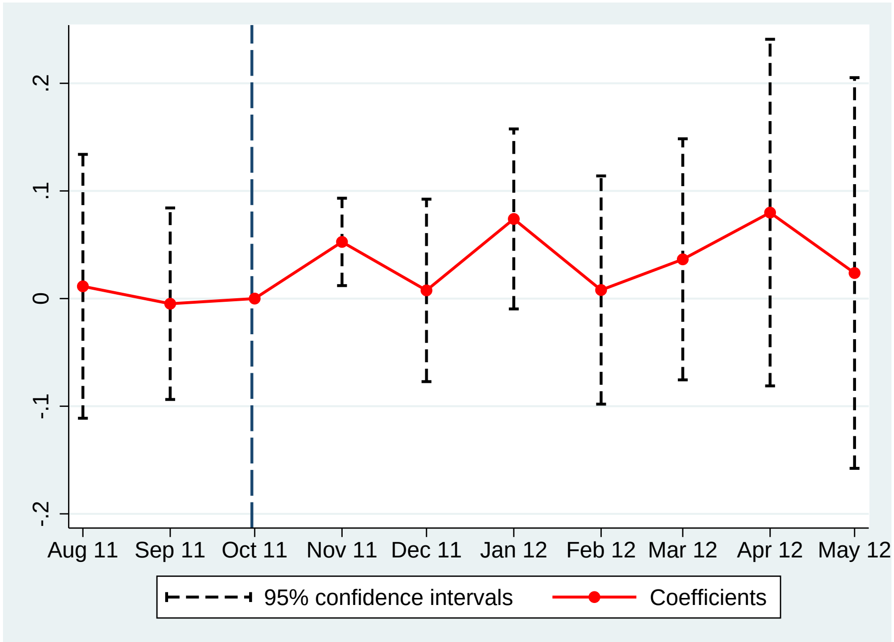


Figure 11: Average Asset Yield.
Notes: The panel above plots the average yield on the assets issued by European institutions that have above (the blue continuous line) and below (the red dashed line) average number of borrowing relationships with MMFs for the period August 2011-May 2012. The vertical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

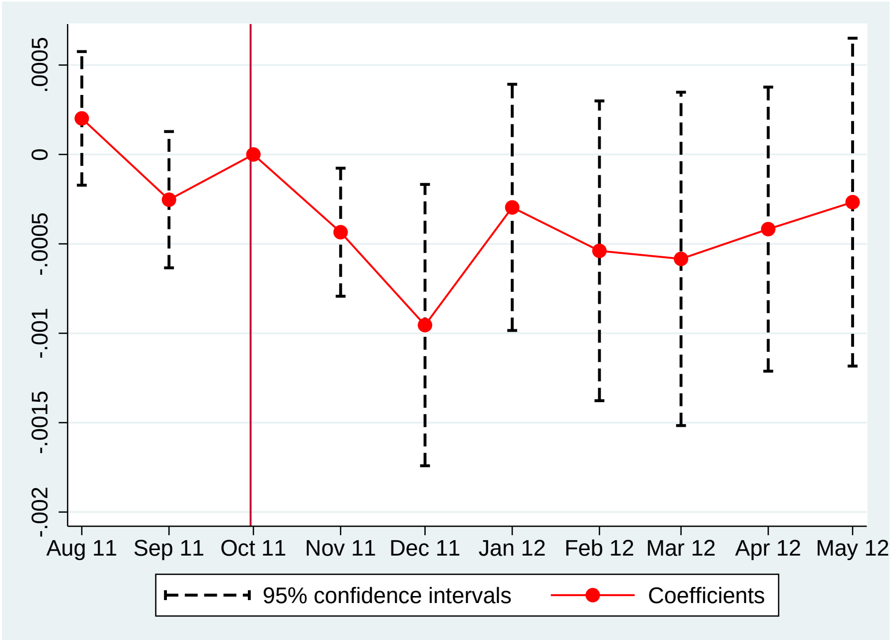
Figure 12: Event Study: Flight from Maturity



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 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.

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

Table 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 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 3: Uncertainty and Strategic Motive

	(1) Δ % AUM Invested	(2) Δ Amount Invested	(3) Δ % AUM Invested	(4) Δ Amount Invested
Number of Ties$_{Aug\ 2011}$ × Post indicator$_{Oct\ 2011}$	0.00252***	118,425**		
	(0.000706)	(58,415)		
Number of Ties$_{Aug\ 2011}$ × Post indicator$_{Feb\ 2012}$			-0.00176***	-100,312*
			(0.000604)	(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 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***	289,519***		
	(0.00143)	(98,146)		
Number of Ties$_{Aug\ 2011}$ × Post indicator $_{Feb\ 2012}$			-0.00489***	-109,737
			(0.00122)	(118,248)
Issuer CDS	-0.000459	-71.97	0.0232	144,948
	(0.00122)	(88,128)	(0.0161)	(231,731)
Issuer CDS× Post indicator $_{Oct\ 2011}$	-0.00260***	-184,804***		
	(0.000605)	(43,200)		
Issuer CDS× Post indicator $_{Feb\ 2012}$			0.00241**	11,634
			(0.000865)	(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 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.

Table 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 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***	0.00626***	0.00621***
	(0.00138)	(0.00166)	(0.00122)
Issuer CDS	-0.000457	0.000680	-0.000569
	(0.00126)	(0.000730)	(0.00125)
Issuer CDS× Post indicator$_{Oct\ 2011}$	-0.00259***	-0.00303***	-0.00233***
	(0.000657)	(0.000862)	(0.000608)
Breaking the Buck	-14.97		-19.82
	(144.0)		(161.0)
Breaking the Buck× Post indicator$_{Oct\ 2011}$	28.51		36.30
	(225.6)		(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 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 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***	0.00632***	0.00736**
	(0.00188)	(0.00224)	(0.00282)
Average Yield Issuer	-0.0441	-0.159	-0.154
	(0.632)	(0.498)	(0.433)
Average Yield Issuer× Post indicator$_{Oct\ 2011}$		0.245	0.307
		(0.462)	(0.414)
Average Maturity Issuer	0.00807	0.00826	0.00400
	(0.00787)	(0.00600)	(0.00497)
Average Maturity Issuer × Post indicator$_{Oct\ 2011}$		0.000464	-0.000818
		(0.00566)	(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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