

# Market Turmoil and Destabilizing Speculation

Marco Di Maggio\*

Massachusetts Institute of Technology

[dimaggio@mit.edu](mailto:dimaggio@mit.edu)

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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. Moreover, I show that a reduction in trading frictions leads to more severe fluctuations in asset prices. At the root of this result are the strategic complementarities between speculators expected to follow similar strategies in the future. Using a novel dataset on MMFs’ portfolio holdings during the European debt crisis, I gauge the strength of funds’ strategic interactions as the number of funding relationships each issuer has with MMFs. I show that funds are more likely to liquidate the securities of issuers that have fewer funding relationships with other funds, obliging them to borrow at shorter maturity and higher interest rates.

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# 1 Introduction

Uncertainty has dominated financial markets of late. The most striking example is the sovereign debt crisis in Europe, but as the market volatility index (VIX) shows, US financial markets experienced similar periods of high uncertainty in the periods surrounding the failure of Lehman Brothers, in the aftermath of 9/11, and following the default of Long-Term Capital Management in 1998 (Figure 1). 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.<sup>1</sup> 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.<sup>2</sup> 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 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

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<sup>1</sup>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)).

<sup>2</sup>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.

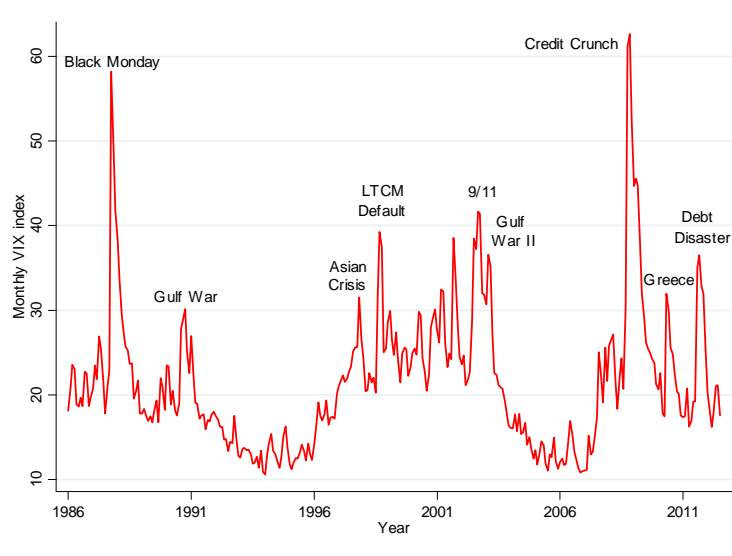


Figure 1: Monthly U.S. stock market implied volatility. Notes: Chicago Board Options Exchange VXO index of percentage implied volatility, on a hypothetical at-the-money S&P500 option 30 days to expiration, from 1986 onward. A new methodology was introduced on September 22, 2003. See the CBOE website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

“*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. That is, in this equilibrium the speculators destabilize the market even when the asset’s value is unaffected, as speculators could continue to hold the asset and capture its cash flow. Interestingly, less trading friction is associated with sharper price decline and faster recovery once the shock hits.

To determine under what conditions such destabilizing trading is most likely to emerge, I investigate the market characteristics that affect investors’ incentives and influence which equilibrium emerges. I derive three main predictions. First, when uncertainty is short-lived speculators have a greater incentive to liquidate before the shock, as the period during which 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 issuers 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 control for issuer-fixed effects in all of the specifications. Additionally, to account for the possibility that the rise in uncertainty in October 2011 affected issuers differently, 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.”<sup>3</sup> 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”.<sup>4</sup> 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 extends the model to study the effect of the introduction of a transaction cost such as a Tobin tax. Section 3.5 presents my uniqueness result and the result on market fragility. Section 4 gives evidence for the main mechanism hypothesized and Section 5 weighs the different motivations underlying funds’ strategies. Section 6 provides further insights on funds’ trading behavior during the European debt crisis by exploiting cross-sectional variation across funds. Section 7 presents additional empirical predictions. Finally, Section 8 discusses the findings and concludes. The online appendix contains the proofs.

## 1.1 Related Literature

This paper is related to several strands of literature. Fundamentally, it is part of the search literature following Duffie et al. (2005), and Duffie et al. (2007), which treats liquidity shocks (as captured by a shift in the preferences of all market participants in the spirit of Grossman and Miller (1988)) in secondary markets with trading frictions. The most closely related papers are Weill (2007) and Lagos et al. (2011), which consider out-of-steady-state dynamics and dealers’ liquidity provision when dealers can hold inventories *in response to* an aggregate liquidity shock of the same type as in Duffie et al. (2007).<sup>5</sup> 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

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<sup>3</sup>“More Trouble For Euro Banks: Money Market Funds Cut Exposure By 37%”, *Forbes*, 21 October, 2011.

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

<sup>5</sup>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.

price even beyond the real effect of the shock.<sup>6</sup>

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

This paper also enriches the literature on financial market runs and feedback effects. [Bernardo and Welch \(2004\)](#) study how dealers provide liquidity during a market run in a model in the tradition of [Diamond and Dybvig \(1983\)](#). [Morris and Shin \(2004\)](#) analyze a model in which traders with short horizons and loss limits interact in a market with long-horizon traders. [He and Xiong \(2012\)](#) analyze dynamic debt runs in a continuous-time model in which creditors must decide whether to roll over their loans to a bank at discrete points in time and, unlike standard models of runs, derive a unique equilibrium. The focus on the timing of arbitrage trades connects my work to [Abreu and Brunnermeier \(2002\)](#) and [Abreu and Brunnermeier \(2003\)](#). These authors analyze a model in which the emergence of a gap between the price and the fundamental value of an asset is exogenously given and informational asymmetries cause a problem of coordination over the optimal time to exit the market. In my model instead, information is symmetric, the price is endogenous, and the focus is on speculators' responses to an increase in uncertainty. Unlike these papers, my model assumes that what generates complementarities among speculators is an uncertainty shock, which exacerbates negative shocks by increasing endogenous volatility. I also estimate the impact of speculators' behavior on issuers' balance sheets, showing that issuers are forced to borrow at higher rates and shorter maturities.<sup>8</sup>

Finally, my paper is part of a large literature that has identified factors that limit arbitrageurs' ability to prevent mispricing: noise-trading risk ([De Long et al. \(1990\)](#)), fundamental risk ([Campbell and Kyle \(1993\)](#)), principal-agent problems ([Shleifer and Vishny \(1997\)](#)), coordination risk ([Liu and Mello \(2011\)](#)), information barriers ([Bolton et al. \(2011\)](#)), slow-moving capital ([Mitchell et al. \(2007\)](#), [Duffie \(2010\)](#) and [Duffie and](#)

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<sup>6</sup>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).

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

<sup>8</sup>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.

Strulovici (2011)), and wealth effects (Xiong (2001), Kyle and Xiong (2001), Gromb and Vayanos (2002), and Kondor (2009)). Compared with earlier research, I posit a different source of the limits to arbitrage – namely uncertainty about future market shocks in conjunction with trading frictions. The paper complements the literature by providing a new set of empirical predictions, which I test in Section 4.

## 2 Model

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

*Environment.* Time is continuous, runs forever and is indexed by  $t \geq 0$ . There is one asset and one perishable good, used as a numéraire. The asset is durable and in supply  $S(t) > 0$ , and its price is denoted by  $p(t)$ . The asset generates a constant cash flow stream, i.e.  $\delta dt$  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 only trade up to a ceiling number of shares. Speculators can hold at most one unit of the asset and cannot sell short, i.e.  $a \in [0, 1]$ .<sup>9</sup> 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.

*Trading Arrangements.* A speculator can trade at random times  $T_\alpha$ , distributed according to a Poisson distribution with intensity  $\alpha > 0$ . The processes are independent across speculators, which means that a fraction  $\alpha dt$  of speculators gets a chance to trade between  $t$  and  $t + dt$ . This friction has several interpretations.<sup>10</sup> First, it

<sup>9</sup>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.

<sup>10</sup>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

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.<sup>11</sup> 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.<sup>12</sup> Third, it might capture settings in which 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 the 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 will not add anything to the insights provided on this by [Lagos and Rocheteau \(2009\)](#).<sup>13</sup>

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

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

depending on current price  $p(t)$ , the market depth  $\lambda$ , and the asset's expected discounted future cash flows  $\frac{\delta}{r}$ .

A larger  $\lambda$  means a steeper demand curve, i.e. lower liquidity by long-term investors. The demand curve (1) is proportional to the spread between the fundamental value  $\frac{\delta}{r}$  and the actual price  $p(t)$ . [Graham \(2003\)](#) calls this spread a safety margin. It represents the net present value of profits to long-term investors when they hold the assets forever and collect the entire future cash flow.<sup>14</sup>

The long-term investors' demand schedule (1) is based on two assumptions. First, it is downward-sloping, since in order to hold more of the risky asset, traders must be rewarded with a lower price. This could be due either to risk aversion or to institutional frictions that make the risky asset less attractive for long-term investors.<sup>15</sup>

The second assumption underlying (1) is that long-term investors' demand depends only on the current price  $p(t)$ . This follows from the assumption that they purchase the asset to hold it to maturity and have only a single opportunity to trade. In other words, they do not attempt to profit from price swings. Such conduct on the part of unsophisticated investors could also follow from the assumption that they lack the information, skills, or time to predict 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

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opportunities arrive with Poisson rate  $\alpha$ , we preclude clustering of trades.

<sup>11</sup>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>.

<sup>12</sup>The explicit introduction of dealers into the model would not affect the analysis.

<sup>13</sup>As is shown by [Lagos and Rocheteau \(2009\)](#), the dealers' fees only reduce the rate at which orders arrive from  $\alpha$  to  $(1 - \eta)\alpha$  where  $\eta$  is the dealer's bargaining power. Instead, in section 3.4, I investigate the introduction of small trading costs, such as a "Tobin tax" on financial transactions.

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

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



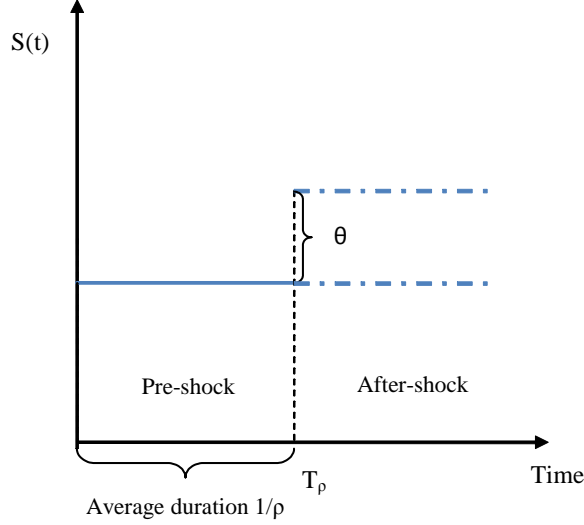


Figure 2: Asset supply might jump at random time  $T_\rho$  due to a negative shock.

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, that tend to hold assets to maturity.<sup>16</sup>

The trading mechanism works as follows. The market clearing price  $p(t)$  solves  $D(p_t) + x(t) = S(t)$ , where  $x(t)$  is the fraction of speculators holding the asset at time  $t$ . Market clearing and equation (1) imply that the price is

$$p(t) = \frac{\delta}{r} - \lambda(S(t) - x(t)). \quad (2)$$

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 (2). Campbell et al. (1993) find evidence consistent with this hypothesis by showing that returns accompanied by high volume tend to be reversed more strongly. Pastor and Stambaugh (2003) provide further evidence for this hypothesis by finding a role for a liquidity factor in an empirical asset-pricing model, based on the idea that price reversals are often provoked by liquidity shortages. Interestingly, Lou et al. (2011) shows that demand/supply shocks have temporary price effects even in the most liquid market of all, that for Treasuries. The mechanism involves the primary dealers, who are required to participate actively and to submit competitive bids in all auctions but whose risk-bearing capacity is limited, as captured in reduced form by (2).

*Negative Shock.* Since we are interested in speculators’ response to negative shocks and in particular in how the strategic interactions among them might actually aggravate rather than mitigate these shocks, I assume that at time  $t = 0$  the speculators become aware that a supply shock might hit the market some time in the future. I assume that at random time  $T_\rho$ , distributed according to a Poisson distribution with intensity  $\rho > 0$ , the market recovers with probability  $1 - \varepsilon$ ; that is, with this probability the shock does not occur. With complementary probability  $\varepsilon$  the market is hit by a shock of severity  $\theta$  that increases supply and accordingly

<sup>16</sup>Notice that while the downward-sloping property of the residual demand function and its dependence only on the current price  $p(t)$  are essential to my analysis, the specific functional form is not.

lowers the price. Hence,  $\theta$  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  $\varepsilon$  can be interpreted as the *level* of uncertainty in the economy.<sup>17</sup> When  $\varepsilon$  is zero, as it is after  $T_\rho$ , speculators do not expect any future shock, but when  $\varepsilon$  becomes positive, as in the interval  $(0, T_\rho)$ , investors are uncertain over the future price path, which affects their trading strategies dramatically.

As Figure 2 shows, once the first shock is realized at  $t = 0$ , speculators are uncertain about future market conditions: with probability  $1 - \varepsilon$  the initial shock is the result of temporary market imbalances, while with probability  $\varepsilon$  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 (2).

## 2.1 Discussion of the Assumptions

The main assumptions of the model are worth some discussion.

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

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.<sup>19</sup> 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.<sup>20</sup> 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.<sup>21</sup> I am interested in the *ex-ante* price effect due to the risk of a future shock, the time-pattern of the price recovery, and the

<sup>17</sup>The assumption that the random time  $T_\rho$  is Poisson-distributed simplifies the analysis by guaranteeing that the speculators’ problem is time-homogeneous.

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

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

<sup>20</sup>Adrian and Shin (2010) find empirical support for this liquidity spiral in data on investment banks.

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

speculators' equilibrium response.

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

Third, I have imposed two restrictions on the severity of the shock  $\theta$ : that it is known at  $t = 0$  and that it remains constant over time. The first restriction can be easily relaxed by assuming that the shock follows a compound Poisson process whose mean jump size is known to market participants. Relaxing the second restriction is the main object of [Section 3.5](#). I shall show that the model can accommodate settings in which the severity of the shock varies over time.

### 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, the strategic interaction is simple: the speculator 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  $T_\rho$ .<sup>22</sup>

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

$$V(a, t) = \mathbb{E}_t \left[ \int_t^{T_\alpha} e^{-r(s-t)} \delta a ds + e^{-r(T_\alpha-t)} \{V(a(T_\alpha), T_\alpha) - p(T_\alpha) [a(T_\alpha) - a]\} \right], \quad (3)$$

where  $T_\alpha$  denotes the speculator's next trading opportunity. The expectation operator is taken with respect to the random variable  $T_\alpha$ . 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

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<sup>22</sup>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.

$1/\alpha$ . The second term is the expected discounted utility of the speculator from the time he next contacts a dealer,  $T_\alpha$ , onward. At time  $T_\alpha$ , 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*

$$u_a = \frac{\delta}{r + \alpha} > q(t), \quad (4)$$

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  $\alpha$ ; whereas  $q(t)$  is the opportunity cost of holding the asset, i.e. the expected discounted forgone capital gain. By reducing the investor's problem to a pointwise maximization, this characterization greatly simplifies the analysis. In other words, after the uncertainty in the market is resolved the speculator's decision is driven by a trade-off between the dividends from holding the asset and the potential capital gain from trading.

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

$$\mathbb{E} \left[ \int_t^{T_\alpha} e^{-r(s-t)} \delta a^U ds - \left( p(t) - e^{-r(T_\alpha-t)} p(T_\alpha) \right) a^U \right], \quad (5)$$

where the price at the next trading time  $T_\alpha$  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 investor 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 (5) and expression (4) for the case in which the speculator trades after the shock: namely, a speculator expects that the shock will have occurred by time  $T_\alpha$ , 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*

$$u_a^U = \frac{\delta}{r + \alpha + \rho} > q^U(t), \quad (6)$$

where

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

Intuitively, the utility flow the investor captures during the pre-shock interval  $[0, T_\rho)$  is also discounted by the average duration of this interval (parameter  $\rho$ ): the farther in the future the shock is expected (low  $\rho$ ), 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 investor 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 investor can condition his trading decision on the realization of the shock  $\theta$ . The probability of being able to trade before or after the random time  $T_\rho$  will be influenced by the trading frictions captured by  $\alpha$  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  $\alpha$ ) 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 back it back. In the case of the 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  $T_\rho$  making it optimal to buy (or hold) the asset before  $T_\rho$ . 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  $T_\rho$ . 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  $\varepsilon$ , with market depth  $\lambda$ , and if the dividend  $\delta$  is sufficiently small it increases with  $\alpha$ .*

The parameters  $\varepsilon$  influences the expected magnitude of the shock and  $\lambda$  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  $T_\rho$ . Higher  $\rho$  means a shorter average duration of the pre-shock period, which increases the speculator’s incentive to profit from the price swing because the expected time during he forgoes dividends is shorter. A similar intuition explains why an increase in the arrival rate of trading opportunity  $\alpha$  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  $T_\rho$  and then for the equilibrium during the pre-shock period, i.e. prior to  $T_\rho$ . 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  $(\{a^U(t)\}, \{a(t)\}, \{p(t)\})$  that satisfies (4), (6) and market clearing (2) 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,

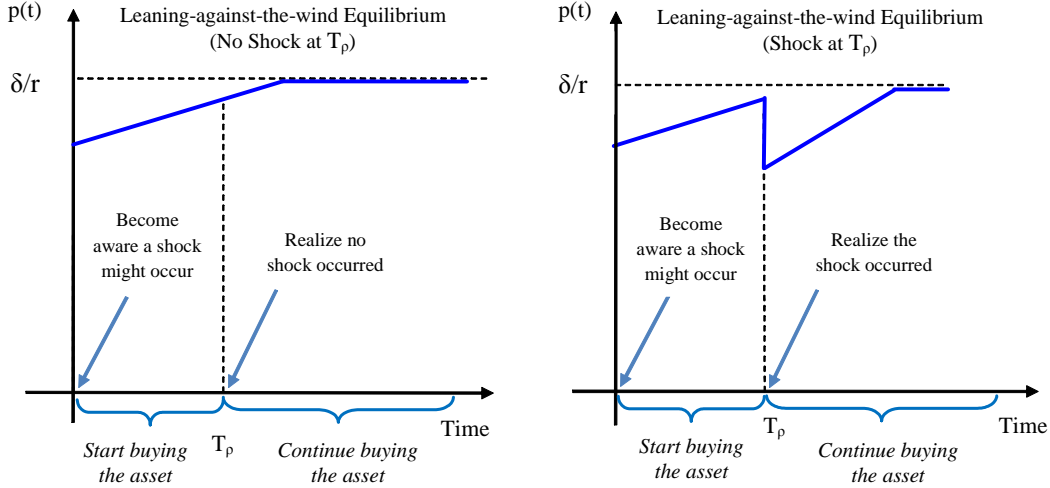


Figure 3: The price path in a “*leaning-against-the-wind*” equilibrium where the shock does not occur (left panel) and where it does (right panel) at random time  $T_\rho$ .

depending on the parameters, either type of equilibrium can emerge when speculators interact and then derive a unique equilibrium in Section 8 by positing that the speculators’ perceptions of the severity of the crisis  $\theta$  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

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

that is, the price rises if speculators start buying and falls over time at rate  $\alpha$  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  $\alpha$ . In the “*cashing-in-on-the-crash*” equilibrium, it falls at rate  $\alpha$  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  $T_\rho$  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  $(T_\rho, \infty)$ ; 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  $\alpha$  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  $\alpha$  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.

Now I am ready to show my 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  $\underline{\theta}(p(t)) < \bar{\theta}(p(t))$ .*

Proposition 2 parameterizes the model according to the severity of the shock  $\theta$  and identifies two dominance regions: one for which it is always optimal to buy ( $\theta < \underline{\theta}(p(t))$ ) and the other in which it is optimal to sell ( $\theta > \bar{\theta}(p(t))$ ), regardless of what other speculators may do in the future. In the intermediate region, namely for  $\theta \in [\underline{\theta}(p(t)), \bar{\theta}(p(t))]$ , the speculator's response to the increase in uncertainty depends crucially on his expectation of what other speculators will do when they get the opportunity to trade. Intuitively, this proposition highlights the importance of the strategic interactions among speculators. Their strategies depend critically on what other speculators plan to do in the future. When the price is expected to come down in anticipation of the shock, speculators amplify the shock by provoking a fire sale. In short, negative shocks that are only expected for the future could cause a financial run today.

In a *leaning-against-the-wind* equilibrium, speculators start providing liquidity to the market by purchasing the asset, which gradually increases the price, although it may plunge at  $T_\rho$  if a shock is realized, as is shown in Figure 3. In expectations 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 the identical expected future shock may have very different present implications depending on the speculators' response.

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

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

**Proposition 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



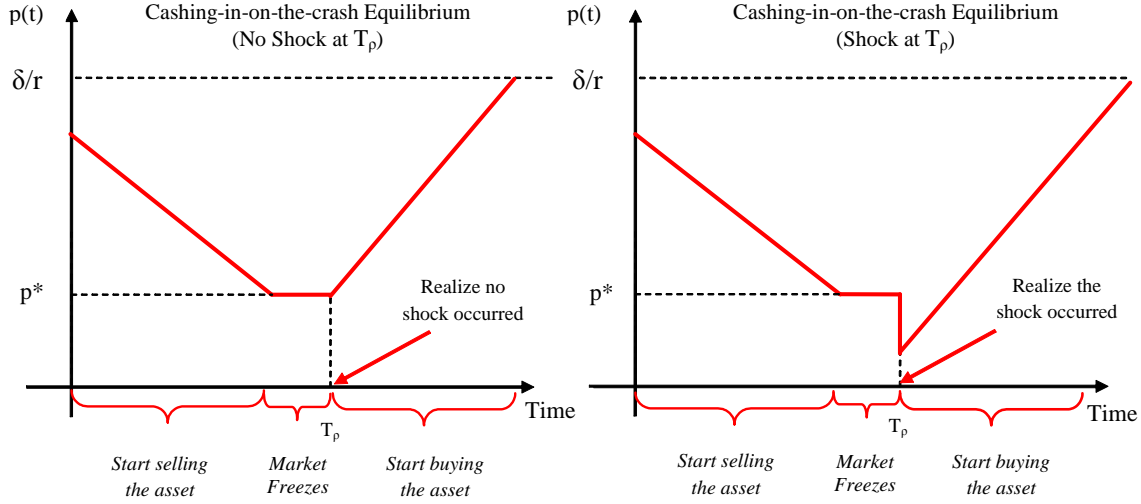


Figure 4: The price path when a “cashing-in-on-the-crash” equilibrium emerges and the shock does not occur at random time  $T_p$  (left panel) and when it does occur (right panel). The flat line in the right panel captures the market freeze when the price reaches the value of  $p^*$ .

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.<sup>23</sup>

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

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

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

and then reverts toward the fundamental value.

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

**Proposition 4 (Trading Frictions and Price Fluctuations)** *In a cashing-in-on-the-crash equilibrium less trading friction, i.e. higher  $\alpha$ , 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  $T_\rho$ . 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 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  $\lambda$ ). Moreover, there exists an  $\underline{\alpha}$  such that the speculators' incentive to sell at  $t < T_\rho$  increases with  $\rho$  if  $\alpha < \underline{\alpha}$ ; while there exists a  $\bar{\rho}$  such that the effect of trading frictions  $\alpha$  is not monotone for  $\rho > \bar{\rho}$ .*

The effects of market depth  $\lambda$  follows from the fact that in less liquid markets the effect of the shock and of the price pressure exerted by other speculators is expected to be greater. This increases the expected capital gains to speculators from strategically selling their holdings at  $t < T_\rho$ . The intuition for the other results in the previous proposition can be better understood by analyzing Figures 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  $\alpha$  and the arrival rate of the shock  $\rho$ . Even if an increase in  $\rho$  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  $\alpha$  and the arrival rate of the shock  $\rho$ . When trading frictions is very great (low  $\alpha$ ) as pictured in Panel (a) the price is expected to decline very

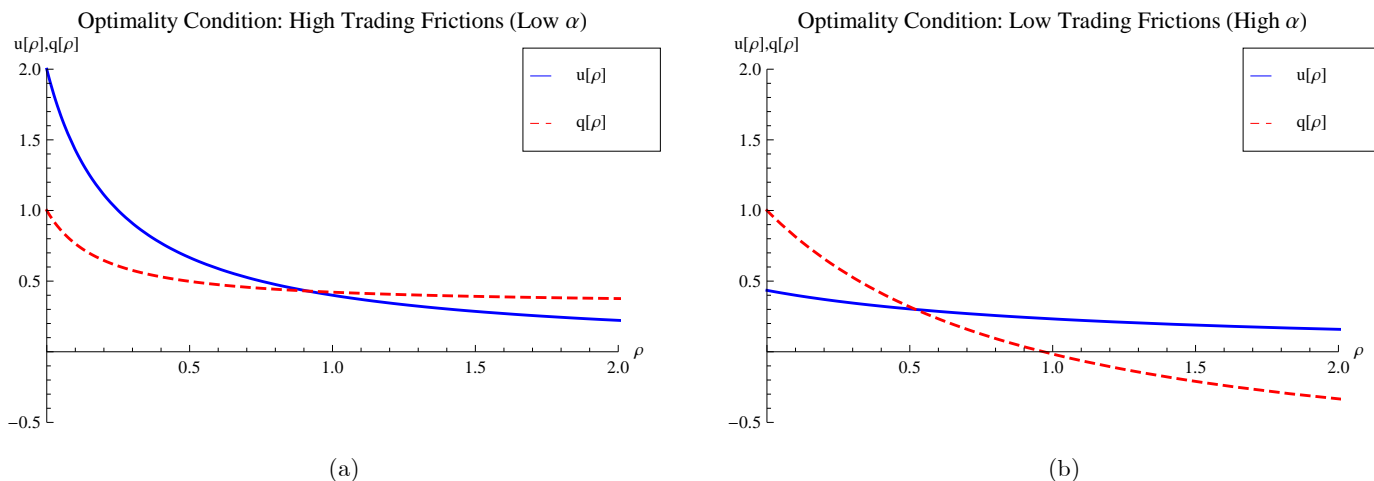


Figure 5: The effect on speculators’ incentives of the persistence of uncertainty  $\rho$  for low and high value of the trading frictions  $\alpha$ .

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  $\rho$  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  $\rho$  is low so that the capital gain  $q(t)$  is greater than the value  $u_a(q)$  obtained by holding the asset.

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  $\alpha$  in two different scenarios: low uncertainty and high uncertainty (measured by the average time  $\rho$  before uncertainty is resolved). Panel (a) shows that if the shock is expected to come very far in the future (low  $\rho$ ), 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  $\alpha$  is very high or very low will speculators sell their holdings, amplifying the effect of the initial shock. Alternatively, when  $\alpha$  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  $\rho$  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

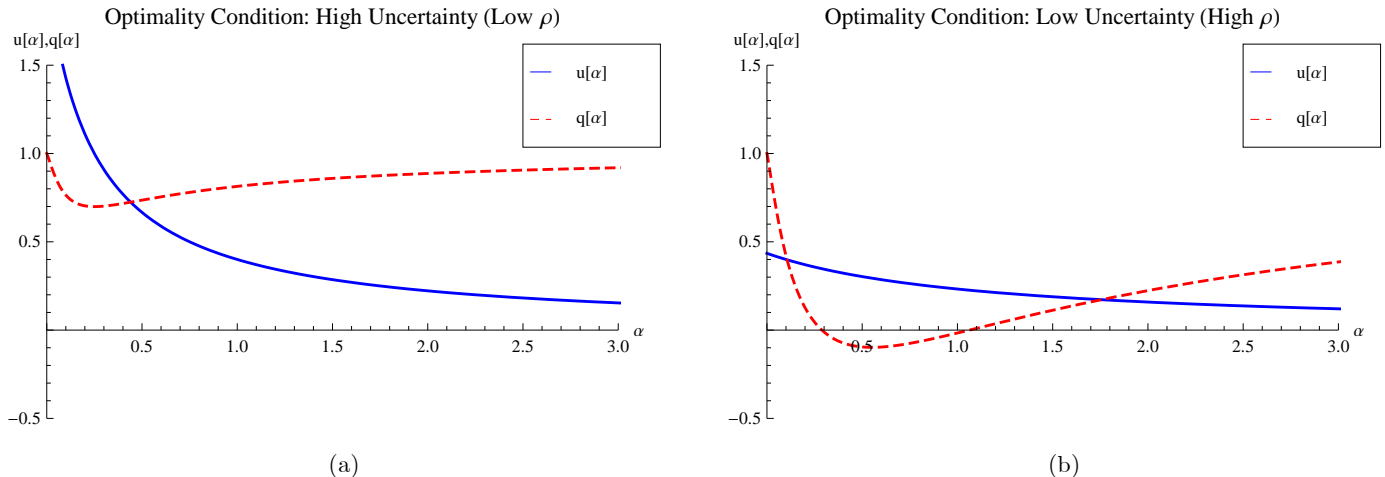


Figure 6: The effect of trading frictions  $\alpha$  on speculators' incentives for low and high values of the persistence of uncertainty  $\rho$ .

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  $\alpha$ , and speculators will prefer to buy the asset and enjoy its dividend flows rather than selling it.

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

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

<sup>24</sup>“Findings Regarding the Market Events of May 6, 2010”. 2010-09-30.

rapidly back and forth.” This resembles the mechanism proposed in my model. While some firms exited the market, high-frequency firms that remained in the market exacerbated price declines because they “escalated their aggressive selling during the downdraft.”<sup>25</sup>

### 3.4 Sand in the Wheels: the Tobin tax

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

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

I can extend the analysis proposed in the previous section to analyze the conditions under which speculators decide to liquidate their positions when they are subject to a transaction tax. In the next proposition, I show that the introduction of a tax on financial transactions might reduce the fragility of the market: speculators need to expect a more severe negative shock (higher  $\theta$ ) to induce a cashing-in equilibrium. However, according to Proposition 6 speculators might be induced to refrain from buying if the tax is sufficiently high.

**Proposition 6 (Tobin tax)** *Suppose a speculator who has the opportunity to trade at time  $t$  expects other speculators to sell the asset in the future. A more severe shock  $\theta$  is needed to induce him to sell as well when  $c > 0$ . Moreover, there exists a threshold  $c^*$  such that if  $c > c^*$  the speculators refrain from trading at all.*

Proposition 6 shows that the effect of the tax on financial transactions on speculators’ trading strategies is twofold. On the one hand, it can reduce the gain from selling in response to an increase in uncertainty. In fact, by reducing the capital gains speculators expect to realize from selling and then buying back after the shock, it reduces price volatility. On the other hand, a transaction cost above the threshold  $c^*$  induces speculators to refrain from trading until uncertainty is realized, hoping to buy the asset at a lower price in the event of a shock.

A different argument, based on the trade-off between congestion and liquidity, which sets out the rationale for policies to avoid extreme price movements, has been proposed by Afonso (2011). Specifically, she argues in favor of trading halts and circuit breakers that interrupt trading when there is a significant imbalance between buy and sell orders or when asset prices decline beyond trigger levels.<sup>26</sup> These instruments, by increasing search

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<sup>25</sup>See “How a Trading Algorithm Went Awry” published by the *Wall Street Journal* on October 2, 2010.

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

frictions during downswings, reduce the effect of congestion, resulting in a lower price discount and in a more liquid market. My result does not depend on negative externalities between speculators – the congestion effect – but follows from the impact of the transaction cost on capital gains: it is more costly for the speculators to exploit temporary price fluctuations. Moreover, Proposition 6 shows that the reduction in fragility might be achieved at the cost of diminishing participation of speculators. This means that even if in equilibrium speculators would have purchased the asset from  $t = 0$  onwards, if the tax is excessive they might not.

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

**Proposition 7 (Tobin tax and liquidity)** *There exists a  $\bar{\lambda}$  such that if the introduction of a transaction cost  $c$  increases  $\lambda$  above  $\bar{\lambda}$ , then a Tobin tax increases the speculators’ incentive to sell at  $t < T_\rho$ .*

Proposition 7 follows from the comparative statics results in Proposition 5: since speculators have a greater incentive to amplify market shocks in less liquid markets, if the tax on financial transactions reduces participation by long-term investors, speculators expect to make more capital gains by selling in response to the uncertainty shock. Hence, the previous proposition highlights an important factor to weigh in seeking to understand the effectiveness of a Tobin tax: how to target such a measure to speculators and not to potential liquidity providers.

### 3.5 Equilibrium Uniqueness

*Overview.* The baseline version of the model, which assumes that all speculators have the same information about the severity of the shock  $\theta$  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  $\theta$ , 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 severity of the shock  $\theta$  starts at a value  $\theta_0 > 0$  time  $t = 0$  and then evolves according to the commonly observed Brownian motion<sup>27</sup>

$$d\theta_t = \mu dt + \sigma dW, \tag{7}$$

where  $\mu$  and  $\sigma$  are constants.<sup>28</sup> The trend  $\mu$  captures how the mean changes over time; the variance  $\sigma$  measures the size of the random component, specifically, how quickly  $\theta$  spreads out. This captures the idea that investors

<sup>27</sup>Frankel and Burdzy (2005) show that a similar argument can be used when  $\theta$  follows an arbitrary mean-reverting process, as long as the drift is a linear function of the state.

<sup>28</sup>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).

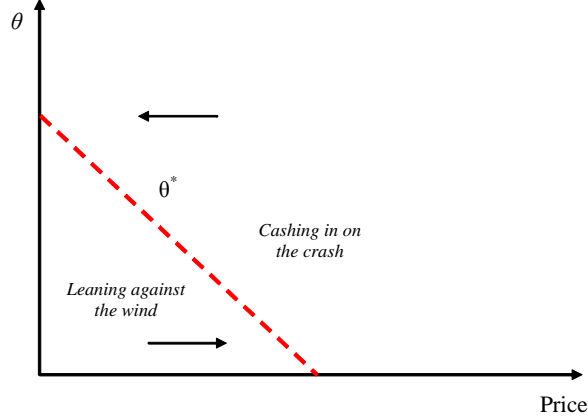


Figure 7: The unique equilibrium

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  $\sigma$ ) or quickly (high  $\sigma$ ). Introducing this dynamic aspect of severity creates heterogeneity in the conditions under which speculators trade. Those trading at time  $t$  might observe a different  $\theta$  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.  $\theta$  might increase.

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

**Proposition 8 (Unique Equilibrium)** *When the severity of the shock  $\theta$  follows (7) then there exists a unique threshold  $\theta^*(p(t))$ , such that cashing in on the crash is optimal if and only if  $\theta > \theta^*(p(t))$ ; while leaning-against-the-wind emerges as an equilibrium for  $\theta < \theta^*(p(t))$ .*

Figure 7 describes the main intuition behind the proposition. At the right of the threshold  $\theta^*$  speculators start liquidating their position; while when they expect the severity of the shock to be smaller than  $\theta^*$ , 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  $\theta^*$  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  $\theta$  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  $\theta^*$  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  $\theta^*$  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  $\theta^*$ , 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  $\theta^*$  depends on the equilibrium price and this is highlighted by the next property.

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

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



## 4 Empirical Analysis

### 4.1 Overview

To assess the impact of uncertainty on investors' behavior empirically and in particular to test whether investors can amplify market shocks, one must identify an exogenous shock to the level  $\varepsilon$  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 consistent with 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.”<sup>29</sup>

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

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

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

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

## 4.2 Bringing the Model to the Data

My quasi-experiment is the spike in uncertainty about the future of the euro area, which represents the  $\varepsilon$  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 calling for a referendum on the rescue plan agreed upon just days earlier.

I can also identify, in my sample, the time when the uncertainty was resolved. In February 2012 the European Central Bank introduced its second long-term refinancing operation (LTRO) to pump liquidity into the banking system. The first LTRO 3-year tender in December 2011 had an uptake of €489 billion, of which about €300 billion was used to retire loans taken out via shorter-term ECB lending facilities and only about €190 billion created fresh liquidity. In February 2012, the ECB held a second auction providing euro-area banks with another €529.5 billion for a period of three years at a rate of just 1 percent. This second LTRO auction saw 800 banks take part, compared with 523 in the December auction. Since these operations by the ECB were recognized as crucial to improving the stability of European financial institutions, I posit that uncertainty fades February 2012, which matches the time  $T_\rho$  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. 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 5 analyzes possible alternative mechanisms to explain the results.

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

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

In the model, absent the uncertainty shock at time zero (i.e.  $\varepsilon = 0$ ), speculators would behave in exactly the same way as long-term investors, namely buy as long as the asset's price is below the fundamental value. The empirical challenge, then, is to find a source of heterogeneity across funds that might induce some to take advantage of the fluctuations in the market. In Section 6 I show that funds' portfolio liquidity is a good proxy for incentives to do this. The idea is that funds that have a large part of their portfolio maturing soon will not be interested in exploiting the temporary mispricing, as they can just wait for the asset to mature to capture the final payoff. But a fund with a less liquid portfolio has a stronger incentive to rebalance, in order to take advantage of this period and I show that the less liquid funds are in fact the treatment group of interest.

Finally, if funds have a mainly strategic incentive to sell off assets and plan to pinpoint the time when the market bottoms out, we should find that they adjust their portfolios after the uncertainty shock of October 2011 in order to be able to get back into the market at the best time. The model developed in section 2 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  $\phi$  at  $t = 0$  by paying a fixed cost  $\xi$ , 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  $T_\alpha$  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  $\xi$  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.

### 4.3 The Institutional Setting: Money Market Funds

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

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

In January 2009, after a tumultuous year for money market funds, the SEC voted to amend the 2a-7 rules to strengthen money market funds. The new rules seek to limit the risk and on enhance fund disclosures. For instance, funds are now required to have enhanced reserves of cash and readily liquidated securities to meet redemption requests, and they can invest only 3 percent (down from 5 percent) of total assets in tier-2 securities, the term on which is limited to a maximum maturity of 45 days.

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

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

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

The surge in market uncertainty in Europe, mostly associated with the sovereign credit risk of Greece, Spain,

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

#### 4.4 Data and Summary Statistics

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

Table 1 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 5% 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.

#### 4.5 Empirical Strategy and Main Results

The micro nature of the data is essential to my econometric identification of the impact of uncertainty on the MMFs incentives. This feature essentially enables me to exploit not just time-series but cross-sectional

variation across issuers and funds to evaluate how the latter reallocate their investments when uncertainty spikes, separately from other possible confounding factors driving MMFs behavior.

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

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

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

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g, Aug\ 11} \times Post + \varepsilon_{i,t}, \quad (8)$$

where  $\Delta Invested_{i,g,t}$  is the change in the fraction of assets under management, or the change in the amount invested by fund  $i$  at time  $t$  in the asset issued by institution  $g$ . I estimate (8) 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 (8) for the period October 2011-May 2012; in this case the *Post* variable is an indicator variable equal to 1 after February, 2012.  $\gamma_t$  denotes time-fixed effects, but I also include issuer-fixed effects  $\phi_g$ . 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.<sup>31</sup> The coefficient we are interested in is  $\beta_1$ , 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  $\beta_1$  is positive and significant, even controlling for time and issuer-fixed effects. Intuitively, during this period the funds were diminishing their exposure to the euro area, but Columns (1) and (2) show that they tended to reduce their investment in the liabilities of issuers with fewer funding relationships, i.e. those for which the complementarity with other funds was stronger. The results are also economically significant: a one-standard-deviation decrease in the number of relationships would decrease the funds' exposure

<sup>30</sup>I have estimated the same regression model (8) using the whole dataset and focusing on the triple interaction between *Issuer Number Ties*, the *Post* indicator and a dummy variable equal to 1 for holdings in the euro area; the results were similar.

<sup>31</sup>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.

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  $\beta_1$  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:

$$\Delta Invested_{i,g,t} = \gamma_t + \phi_g + \beta_1 Issuer\ Ties_{g, Aug\ 11} \times Post + \alpha_1 Issuer\ CDS_{g,t} + \alpha_2 Issuer\ CDS_{g,t} \times Post + \varepsilon_{i,t} \quad (9)$$

which is the same as in (8) except for the fact that now I control for the issuer CDS and its interaction with the two *Post* indicator variables for the two sample periods.

Columns (1) and (2) reveal two noteworthy findings. First, risk-related considerations are indeed important in explaining money market funds' behavior, especially in the post-uncertainty shock period, as is underscored by the significance at the 1% level of the coefficient  $\alpha_2$ . Intuitively, when uncertainty spikes funds tend to disinvest more from the issuers whose riskiness has increased as a consequence. Second, the coefficient  $\beta_1$ , 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.

## 4.6 Consequences for Issuers

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

I consider two natural proxies to measure how hard it is for issuers to get funding during my sample period: the maturity of their funding agreements and the yields they have to pay to compensate the MMFs. Intuitively, it might be harder for an issuer to obtain funding if he needs to borrow at shorter maturity, (say, overnight repos), and if the interest rate that he needs to pay is higher. Suggestive evidence that this is the case is provided by Figures 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:

$$Issuer\ Maturity_{g,t} = \beta_1 Issuer\ Ties_{g, Aug\ 11} \times Post + \gamma_t + \phi_g + \varepsilon_{g,t}, \quad (10)$$

where the dependent variable is the average maturity of the assets sold by issuer  $g$  at time  $t$ . As in the previous regression model (8), I control for time- and issuer-fixed effects, to account for the effects of time-varying demands for short-term funding and for the differences in issuers' characteristics, such as size, creditworthiness and access to other forms of credit.

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

## 5 Alternative Explanations

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

### 5.1 Fund Distress

The financial crisis highlighted the potential risks associated with money market funds. On September 16, 2008, because of its exposure to Lehman Brothers' debt securities, the Reserve Primary Fund "broke the buck". It entered into a prolonged liquidation process, ultimately 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 (8)

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

where the coefficient  $\alpha_2$  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 (8) and exclude the funds with a NAV below 1, approximately 20% of my sample. Column (2) of Table 7 demonstrates that the coefficient  $\beta_1$  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 (11) excluding them; the previous findings again stand confirmed.

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

## 5.2 Diversification Motive

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

<sup>32</sup>Duygan-Bump et al. (2012) analyze the effectiveness of this intervention in detail.

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 (9) both for the funds with below-average and above-average exposure to the euro area. The idea is that funds are more likely to liquidate their holdings of institutions with fewer funding relationships if they already have high exposure to the euro area. Columns (1) and (2) of Table 8 show the results for the funds with low exposure, Columns (3) and (4) those for the funds with high exposure. In Columns (1) and (3) the dependent variable is the change in the fraction of assets under management invested in the assets of issuer  $g$ , while Columns (2) and (4) consider the effect on the amount invested. The effect of the number of ties is still positive and significant in Columns (1), (3) and (4). The lack of significance in Column (3) can be explained by the reduced number of observations. The magnitude of the effect is greater for the funds with below-average exposure to the euro area, as highlighted by the comparison of Columns (1) and (3). This finding suggests that my main results cannot be explained by a desire to diversify across regions.

Second, I include the number of different European issuers that are held in the fund's portfolio in the regression. The idea is that a fund that has invested in very few European issuers might be extremely susceptible to changes in the market value of these securities and might behave differently from a fund with better diversified portfolio. Column (5) shows that more diversified funds tend to increase their exposure to these European issuers. However, the coefficient  $\beta_1$  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.

### 5.3 Differences in Market Liquidity

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

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

I measure liquidity in three alternative ways. I observe the maturity and yields of the assets of different issuers. The idea is that an asset of longer maturity is harder to sell at a fair price (Edwards et al. (2007) and Bao et al. (2011)). Similarly, the liquidation risk is partly reflected in the yields that funds require to hold the assets. So on this logic, as an additional control I include in my main regressions the average maturity and yield of the assets issued by institution  $g$  (result in Column (1) of Table 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.

## 6 Who are the Speculators?

This section investigates which types of funds are more likely to exploit increased uncertainty, with evidence in support of Hypotheses 2 and 3. The hypothesis suggested by the model is that the funds that are more prone to sell their holdings when uncertainty spikes are those most affected by short-term fluctuations. This suggests

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<sup>33</sup>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.

that the incentives to capture capital gains are greater if the fund’s portfolio has longer maturity, which will allow it to profit from price swings. The idea is: a fund that has 80% of its assets maturing within seven days has less incentive than one that has only 30% maturing. In fact, the latter is affected more severely by the negative shock and may opt to liquidate some of its holdings early in order to buy them back at a better price.

The foregoing suggests that the fraction of assets maturing within seven days might be a good proxy for the fund’s incentive to take advantage of market fluctuations. This is highlighted in Table 2, which shows the summary statistics for the main fund characteristics for short-maturity and longer-maturity funds. The latter are usually larger in terms of AUM and invest more in riskier asset classes, ABCP, bank obligations (both domestic and foreign banks) and significantly less in U.S. treasuries and repos. Moreover, funds with less liquid portfolios are more likely to be institutional than retail funds. This finding suggests that the funds with less liquid portfolios are more sophisticated than those with more liquid portfolios and so can play the role of speculators in this market.

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

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

$$Euro\ Exposure_{i,t} = \gamma_t + \eta_i + \beta_1 Post_{Oct\ 2011} \times Liquidity_{i,Aug\ 2011} + \delta \mathbf{X}_{i,Aug\ 2011} + \varepsilon_{i,t}, \quad (12)$$

where  $Euro\ Exposure_{i,t}$  is the main dependent variable and is defined as the fraction of assets invested in the euro area by fund  $i$  in month  $t$ ,  $\eta_i$  denotes fund-fixed effects, and  $\gamma_t$  denotes time-fixed effects.  $Post_t$  is an indicator variable equal to 1 after October 2011, which identifies the high-uncertainty period.  $Liquidity_{i,Aug\ 11}$  is the fraction of assets maturing within seven days, as of August 2011. When I do not control for fund-fixed effects, I include  $\mathbf{X}_{i,Aug\ 2011}$ , a vector of fund-specific controls that includes size, average annualized gross 7-day yield, and the fraction of assets invested in repos, U.S. Treasury securities and foreign bank securities. These variables control for the observed differences across funds, which might be correlated with their behavior in the post period. Both the liquidity variable and the other controls are measured as of August 2011, which mitigates any concern that investment choices are driven by changes in fund characteristics because of variations in uncertainty in the post-period. Since the exposure to the euro area is a fund-specific attribute, it is possible that it is serially correlated. To address this concern, I cluster standard errors at the fund level. The coefficient of interest is  $\beta_1$ , which measures the differential impact of uncertainty on the more liquid funds’ exposure to the euro area relative to that of the less liquid ones.

I begin with a nonparametric analysis of the observed effects. For each month between August 2011 and

May 2012, I estimate the coefficient from the cross-sectional regression model (12) for Liquidity. Specifically, Figure 16 presents the coefficients  $\beta_\tau$  of the following regression model

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

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

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

Next, I present the results of the difference-in-difference regression corresponding to the non-parametric analysis. Column (1) of Table 10 confirms that in the post-period, funds decreased their exposure to the euro area significantly, by more than 4 percentage points, as is shown by the significance of the Post variable. Moreover, more liquid funds decrease their exposure less than the less liquid ones. The results might be driven by other shocks or news released after October 2011, and to address this question I include time-fixed effects in columns (2)-(6). The results might also be driven by unobserved time-invariant differences among funds that are correlated with liquidity. This issue is addressed by including fund-fixed effects in columns (3)-(6). In all of these specifications, no difference in the quality of the results emerges.

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

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

My method of accounting for this possibility is twofold. First, I include a set of controls that might drive the results and capture (at least partially) heterogeneity across funds. These controls involve a set of fund and portfolio characteristics. The fund characteristics are yield, size, an indicator variable for institutional fund, weighted average portfolio maturity, pre-shock exposure to the euro area, and net asset flow. For instance, large

funds are often thought to be more involved in active risk choices, while smaller funds are often considered simple, cash-parking vehicles with no active risk-management strategy. Or funds' behavior might be driven, at least partially, by redemptions; to account for this possibility, I control for the fund's net flow. Portfolio characteristics controlled for are the fractions of assets invested in foreign bank obligations, repos, ABCP and Treasuries. I include these time-varying characteristics, as measured in August 2011, in Column (2), and also in Columns (4)-(6). Second, in Column (6) I include fund-specific linear trends to check whether allowing for differential trends significantly changes the results in a meaningful way. It does not, further confirming the empirical strategy.

If uncertainty is the main driver of funds' decisions to lend to financial institutions and corporations in the euro area over the short term, the opposite effect should be true when the uncertainty regarding the European debt crisis is attenuated and the funds regain confidence. Accordingly, I investigate whether money market funds resumed euro area asset purchases once uncertainty began to abate in February 2012 or whether they continued to invest exclusively in safe havens such as U.S. Treasury paper. Specifically, I estimate the following regression model, which is the counterpart to 12:

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

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

Table 11 shows that  $\beta_1$  is indeed positive and significant, suggesting an increase of 1.4% in exposure to the euro area after February 2012, which confirms the perceived normalization of the European situation. Moreover, the coefficient of interest,  $\beta_1$ , is negative and significant. This finding suggests that low-liquidity funds increase their holdings in the euro area as uncertainty fades, corresponding to what happens after  $T_\rho$  in the model.

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

## 6.1 Timing the Market

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

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

where the dependent variable  $Liquidity_{i,t}$  is the fraction of fund  $i$ 's asset maturing within seven days. I control for fund- and time-fixed effects and cluster the standard errors at fund level. Table 12 shows that the funds that were less liquid in the pre-period acted like the speculators of my model did in fact begin to increase the liquidity of their portfolio after the October 2011 shock. This confirms Hypothesis 3.

## 7 Additional Empirical Implications

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

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

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

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

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

The evaporation of liquidity (Prediction 1) follows from the “cashing-in” equilibrium of Proposition 3 and is a consequence of the coordinated trading behavior of the speculators highlighted in Proposition 2. The sudden increase in the returns to liquidity-provision, instead, follows from the fact that the fundamental value of the asset is unaffected while its price is driven down by speculation. The sudden evaporation of liquidity was observed in many sectors of financial markets in 2007-09. Gorton and Metrick (2009) proposes the explanation that the crisis amplified asymmetric information problems: that is, several debt instruments became more information-sensitive, which aggravated adverse-selection problems. I propose an alternative, complementary hypothesis: speculators amplified the initial uncertainty shock by reducing liquidity supply because they forecast further shocks and sought to take advantage of them.

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



Prediction 2 follows from speculators’ trade-off between asset cash-flow and capital gains and is discussed in section 3.3. The trading behavior hypothesized seems to be confirmed empirically by Ellul et al. (2012). During episodes of market turmoil – dating back to the 1987 market crash, – Ellul et al. (2012) show that investors with short horizons (as proxied by portfolio turnover) sell their stock holdings to a larger extent than those with longer trading horizons. This creates price pressure on the stocks mostly held by short-horizon investors, which therefore experience larger price drops and sharper reversals than stocks mostly held by long-horizon investors. The evidence indicates that investors with short horizons amplify the effects of negative market-wide shocks, as the model predicts, by demanding liquidity when other potential buyers’ capital is scarce. And these effects are larger when the expected shock, or market uncertainty, is greater (as captured by the comparison between the “black Monday” crash of 1987 and the Lehman Brothers’ collapse in 2008).

My results concerning the role of speculators in stabilizing financial markets related more broadly to a strand of the literature that explores institutional investors’ behavior during financial crises. Ben-David et al. (2012), for instance, show that, only part of hedge funds’ substantial reduction of equity holdings during the crisis in 2008 is explained by the need to meet redemptions.<sup>34</sup> This empirical finding suggests the possibility that at least a fraction of the liquidation is driven by strategic motives.

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

Prediction 3 follows from the Property 3 of the equilibrium presented in Proposition 8, whereas Prediction 4 follows from the comparative statics results presented in Proposition 5. These predictions suggest that the characteristics of the markets play an important if somewhat surprising role in shaping speculators’ incentives. In particular, Prediction 3 posits that amplification of market shock is more likely when the market has just gone through a bout of euphoria, driving prices up. This resembles the mechanism proposed by Brunnermeier et al. (2008) in the analysis of carry trades in exchange markets. Uncertainty shocks have a more severe effect on speculators’ incentives to hold an asset when in the aggregate they are more exposed to it. In the model, this corresponds to the fact that since more speculators are holding the asset at  $t = 0$  and are not able to liquidate instantaneously due to trading friction, it will take time before they have sold all their holdings. This increases the expected capital gains to speculators from continuing to trade in the same direction as the shock.

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

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

that have relatively high temporary price impact.

## 8 Conclusion

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

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

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

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

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

Given the central role that the housing market played in triggering the crisis, it is important to understand the determinants of house price dynamics over the recent cycle, as this would inform efforts to enhance financial stability. Recent papers by [Haughwout et al. \(2011\)](#) and [Bayer et al. \(2011\)](#) provide evidence that my mechanism fits this market, where trading friction is significant. [Haughwout et al. \(2011\)](#) identify real-estate

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<sup>35</sup> "Remarks Before the Security Traders Association" (September 22, 2010).

<sup>36</sup> For instance, on December 3, 2009, a "Let Wall Street Pay for the Restoration of Main Street Bill" was introduced in the House of Representatives to levy a tax on securities transactions. Similarly, in September 2011 the European Commission proposed to institute a financial transaction tax in the 27 EU member states by 2014.

investors (as opposed to owner-occupants) as a key factor in the house price surge and crash. They show that at the peak in 2006, in the four states with the most pronounced housing cycles, the investor share was 45 percent. In a similar vein, [Bayer et al. \(2011\)](#) analyze transaction data in the Los Angeles metropolitan area and identify intermediaries that attempt to time the market, showing that their presence is strongly associated with price instability. They argue that both the boom and the bust were driven by these investors or intermediaries (the speculators in my model), who had a much shorter trading horizon than owner-occupants (long-term investors).

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

The third contribution of the paper lies in the empirical analysis of the importance of the mechanism revealed by the model, tested on a novel dataset on MMFs' portfolio holdings during the European debt crisis. I gauge the strength of strategic interactions among funds as the number of funding relationships that each issuer has with money market funds. I show that funds are much more likely to liquidate the assets of issuers that have fewer funding relationships. In other words, price destabilization is greater for assets characterized by greater complementarity among funds. As a result, the maturity of these issuers' assets shortens significantly and yields increase during high-uncertainty periods. These results are robust to alternative explanations based on precautionary or diversification motives for selling and on capital constraints.

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

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

## 9 Appendix A – Proofs

### Proof of Lemma 1.

I can rewrite the value function (3) as

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

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

$$\max_{a' \geq 0} \int_t^{T_\alpha} e^{-r(s-t)} \delta a' ds - \left\{ p(t) - \mathbb{E} \left[ e^{-r(T_\alpha-t)} p(T_\alpha) \right] \right\} a'. \quad (13)$$

The speculator chooses his asset holdings in order to maximize the expected present discounted value of his utility flow net of the expected present discounted value of the cost of holding the asset from time  $t$  until the next time  $T_\alpha$ , when he can readjust his holdings. Then, I compute the first term of (13) as

$$u(a) = \mathbb{E} \left[ \int_0^{T_\alpha-t} e^{-rs} \delta a ds \right] = a \frac{\delta}{r + \alpha}, \quad (14)$$

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

$$\mathbb{E} \left[ e^{-r(T_\alpha-t)} p(T_\alpha) \right] = \alpha \int_0^\infty e^{-(r+\alpha)s} p(t+s) ds. \quad (15)$$

Substitute (14) and (15) into (13) to obtain the formulation of the speculator's problem in the statement of the lemma. ■

### Proof of Lemma 2.

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

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

One sees that this is exactly the same equation as in Lemma 1, except that now  $\alpha$  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  $\tau$  is the next time the speculator will have the opportunity to contact the dealers. This is strictly less than  $\frac{\delta}{r} - p(t)$  because of discounting. Hence, it is optimal to buy the asset back once uncertainty has been resolved, i.e. after  $T_\rho$ .

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  $\theta$  that makes the investor indifferent between buying and selling the asset. Formally, the

indifferent threshold  $\theta^*$  is given by the following expression

$$\begin{aligned}
\frac{\delta}{r + \alpha + \rho} &= [p^U(t) - \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} (e^{-\rho(\tau_\alpha-t)}) p^U(\tau_\alpha) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho-t)} p(\tau_\alpha|\tau_\rho) d\tau_\rho d\tau_\alpha] \quad (16) \\
&= [p^U(t) - \left\{ \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} (e^{-\rho(\tau_\alpha-t)}) p^U(t) \right. \\
&\quad \left. + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho-t)} (\varepsilon(F - \lambda(S + \theta^*)) + (1 - \varepsilon)F) d\tau_\rho d\tau_\alpha \right\}] \\
&= [p^U(t) - \left\{ \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} (e^{-\rho(\tau_\alpha-t)}) p^U(t) \right. \\
&\quad \left. + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho-t)} (F - \varepsilon\lambda(S + \theta^*)) d\tau_\rho d\tau_\alpha \right\}] \\
&= p^U(t) - \frac{\alpha p^U(t)}{r + \alpha + \rho} + \frac{\alpha(F - \varepsilon\lambda(S + \theta^*))}{r + \alpha + \rho} - \frac{\alpha(F - \varepsilon\lambda(S + \theta^*))}{r + \alpha} \\
&= \frac{p^U(t)(r + \rho)}{r + \alpha + \rho} - \alpha(F - \varepsilon\lambda(S + \theta^*)) \frac{\rho}{(r + \alpha + \rho)(r + \alpha)},
\end{aligned}$$

where I have substituted the prices in the different regions and simplified. Notice that as  $\theta$  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  $\delta$ . The effects of the other parameters of interest can be found as follows. First, the effect of the market depth  $\lambda$  on the capital gain in expression (16) is clearly positive as :

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

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

The effect of the persistence of uncertainty is computed as

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

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

Finally, the effect of the trading frictions  $\alpha$  can be computed as follows

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

Then, as long as  $\delta$  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 (2) that the price evolves according to:

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

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

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

which implies

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

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

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

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

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

I can now revert the change of variables to get

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

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

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

which gives as a solution

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

I can follow the same steps shown above for the other case to get the result stated in Lemma 3:

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

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

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

where

$$\tilde{p}(\tau_\alpha) = \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} (e^{-\rho(\tau_\alpha-t)}) p^c(\tau_\alpha) + \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho-t)} p(\tau_\alpha|\tau_\rho) d\tau_\rho d\tau_\alpha. \quad (17)$$

I know that  $p^c(\tau_\alpha) < p^c(t)$  because in this region the price is strictly decreasing. I start simplifying the terms in expression (17); using Lemma 3 we can rewrite the first term as

$$\begin{aligned} & \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} (e^{-\rho(\tau_\alpha-t)}) p^c(\tau_\alpha) d\tau_\alpha \\ &= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha-t)} p^c(\tau_\alpha) d\tau_\alpha \\ &= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha-t)} \left( p^c(t) e^{-\alpha(\tau_\alpha-t)} + (F - \lambda S) (1 - e^{-\alpha(\tau_\alpha-t)}) \right) d\tau_\alpha \\ &= \alpha \left( \frac{p^c(t)}{r + 2\alpha + \rho} + \frac{\alpha (F - \lambda S)}{(r + \alpha + \rho)(r + 2\alpha + \rho)} \right). \end{aligned} \quad (18)$$

The second term in (17) takes into account that the speculator might come into contact with the market after  $T_\rho$ , which means that the price is a weighted average of the price after a shock (with weight  $\varepsilon$ ) and of the price once the shock reveals to be temporary (with weight  $(1 - \varepsilon)$ ):

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



the previous expression also shows that the capital gain  $q^c(t)$  is increasing in  $\theta$ . I can use the previous expression to rewrite the second term in (17) as follows

$$\begin{aligned}
& \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} \left( \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho-t)} p(\tau_\alpha|\tau_\rho) d\tau_\rho \right) d\tau_\alpha \tag{19} \\
&= \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} \left( \int_t^{\tau_\alpha} \rho e^{-\rho(\tau_\rho-t)} \begin{bmatrix} p(t) e^{-\alpha(\tau_\alpha-t)} + (1 - e^{-\alpha(\tau_\alpha-t)}) (F - \lambda S + \lambda) \\ -\varepsilon \lambda \theta (1 - e^{-\alpha(\tau_\alpha-t)}) \end{bmatrix} d\tau_\rho \right) d\tau_\alpha \\
&= \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} \left( p(t) e^{-\alpha(\tau_\alpha-t)} (1 - e^{-\rho(\tau_\alpha-t)}) + (1 - e^{-\rho(\tau_\alpha-t)}) (1 - e^{-\alpha(\tau_\alpha-t)}) (F - \lambda S + \lambda) \right. \\
&\quad \left. - \varepsilon \lambda \theta (1 - e^{-\rho(\tau_\alpha-t)}) (1 - e^{-\alpha(\tau_\alpha-t)}) \right) d\tau_\alpha \\
&= (\alpha p^c(t) \left( \frac{\rho}{(r+2\alpha)(r+2\alpha+\rho)} \right) + \alpha (F - \lambda S + \lambda) \left( \frac{\alpha}{(r+\alpha)(r+2\alpha)} - \frac{\alpha}{(r+2\alpha+\rho)(r+\alpha+\rho)} \right) \\
&\quad - \alpha \varepsilon \lambda \theta \left( \frac{\alpha}{(r+\alpha)(r+2\alpha)} - \frac{\alpha}{(r+2\alpha+\rho)(r+\alpha+\rho)} \right)).
\end{aligned}$$

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

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

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

$$\underline{\theta}(p(t)) = \left[ \frac{\delta}{r+\alpha+\rho} - p^c(t) \left( 1 - \left( \frac{\alpha \rho}{(r+2\alpha)(r+2\alpha+\rho)} \right) \right) - \alpha (F - \lambda S + \lambda) \mathbb{H} \right] \frac{1}{\alpha \varepsilon \lambda \mathbb{H}}. \tag{20}$$

Following similar steps to the previous case, I can find the conditions under which buying is optimal by supposing that for  $t \in [0, T_\rho)$  the price is expected to rise and check that it is individually optimal to buy the asset rather than selling. Formally, I can substitute in expression (17) the different expected price path:

$$\begin{aligned}
& \int_t^\infty \alpha e^{-(r+\alpha)(\tau_\alpha-t)} (e^{-\rho(\tau_\alpha-t)} p^c(\tau_\alpha)) d\tau_\alpha \tag{21a} \\
&= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha-t)} p^c(\tau_\alpha) d\tau_\alpha \\
&= \int_t^\infty \alpha e^{-(r+\alpha+\rho)(\tau_\alpha-t)} \left( \lambda - (\lambda - p(t)) e^{-\alpha(\tau_\alpha-t)} + (F - \lambda S) (1 - e^{-\alpha(\tau_\alpha-t)}) \right) d\tau_\alpha \\
&= \frac{\alpha \lambda}{r+\alpha+\rho} - \frac{\alpha \lambda}{r+2\alpha+\rho} + \frac{\alpha p(t)}{r+2\alpha+\rho} + \frac{\alpha (F - \lambda S)}{r+\alpha+\rho} - \frac{\alpha (F - \lambda S)}{r+2\alpha+\rho} \\
&= \alpha \lambda \left( \frac{\alpha}{(r+\alpha+\rho)(r+2\alpha+\rho)} \right) + \frac{\alpha p(t)}{r+2\alpha+\rho} + \alpha (F - \lambda S) \left( \frac{\alpha}{(r+\alpha+\rho)(r+2\alpha+\rho)} \right).
\end{aligned}$$

By substituting (21a) in the optimality condition identified in Lemma 2, I can find a different threshold for the

severity of the shock:

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

This completes part (i).

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

$$\frac{\delta}{r+\alpha+\rho} > p^c(t) - \tilde{p}(\tau_\alpha) \quad (22)$$

Comparing condition (18) with (21a) shows that the threshold  $\bar{\theta}(p(t))$  that solves (22) is higher than  $\underline{\theta}(p(t))$ .

It is now important to notice a key difference of these threshold with the one,  $\hat{\theta}$ , identified in Proposition 1: when speculators interact with each other in the market, the thresholds depend (negatively) on the price at time  $t$ , i.e.  $\frac{\partial\bar{\theta}(p_t)}{\partial p_t} < 0$  and  $\frac{\partial\underline{\theta}(p_t)}{\partial p_t} < 0$ . ■

### 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.<sup>37</sup> 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  $T_\rho$ , which makes it optimal for him to continue to hold the asset.

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

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

After  $T_\rho$ , 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  $T_\rho$  a shock of severity  $\theta$  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  $\tau$  is the next instant at which the speculator has the opportunity to contact the market. This is strictly less than  $F - p(t)$  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

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

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  $\alpha$ , 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  $\alpha$  (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  $\alpha$  and  $\rho$  as depicted by the blue curves in the Figures 5 and 6.

The capital gain in 19, instead, is composed of three terms, and I am going to analyze each one of them.

First we have the effect of parameters on the coefficient of the price is positive:

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

The effect of  $\alpha$  can be similarly computed as follows:

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

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

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

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

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

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

Finally, I can investigate the effect of market depth  $\lambda$ . The effect on 19 is positive if  $(1-S) - \varepsilon\theta > 0$ , which is true for small enough probability of the shock  $\varepsilon$ . ■

### Proof of Proposition 6.

Since the cost lowers the capital gain, it decreases the speculators' incentive to profit from price swings. In other words, the threshold for the shock  $\theta$  that makes the traders indifferent between holding the asset and profit from price swings need to increase. In fact, suppose a speculator meeting coming into contact with the market at time  $t < T_\rho$ , sells the asset if and only if the following condition holds

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

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

To show that the introduction of a transaction cost reduces speculators' incentive to profit from fluctuations, we can follow the same procedure as in Proposition 2, but including the tax  $c$  in the capital gain  $q(t)$ . We can rewrite the problem of an investor who gains access to the market at time  $t$  which has to pay a transaction cost

$c$  as

$$\max_{a' \geq 0} \int_t^{T_{\alpha\rho}} e^{-r(s-t)} \delta a' ds - \left\{ (p(t) + c) - \mathbb{E} \left[ e^{-r(T_{\alpha}-t)} \left\{ (\mathbb{I}_{\{T_{\alpha} < T_{\rho}\}} p^U(T_{\alpha}) + \mathbb{I}_{\{T_{\alpha} > T_{\rho}\}} p^U(T_{\alpha}|T_{\rho})) - c \right\} \right] \right\} a' \quad (23)$$

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

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

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

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

where the second equality follows from Lemma 2.

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

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

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

### Proof of Proposition 7.

The result that the introduction of a Tobin tax might actually increase speculators' incentives to sell the asset at time  $t < T_{\rho}$ , follows from Proposition 5 and the assumption that the liquidity provided by long-term investors,  $\lambda(c)$ , is an increasing function of the transaction cost. In fact, Proposition 5 shows that speculators have higher incentives to sell their holdings in less-liquid markets, namely when  $\lambda$  is high. Suppose now that for a given  $\lambda$ , the condition identified in Lemma 2 would predict them to purchase the asset. Consider now the introduction of the tax, which increases  $\lambda$  to  $\lambda' > \lambda$ ; if the market depth function  $\lambda(\cdot)$  is sufficiently sensitive to  $c$ , such increase might increase the potential capital gains so much that now it is optimal for the speculators to actually sell the asset. Hence, it follows the statement of the proposition that when the introduction of transaction costs reduce the liquidity of the market, this might have destabilizing effects. ■

### Proof of Proposition 8.

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  $\theta_t$  follows an arbitrary mean-reverting process, as long as the drift  $\mu$  is a linear function of the state  $\theta_t$ .

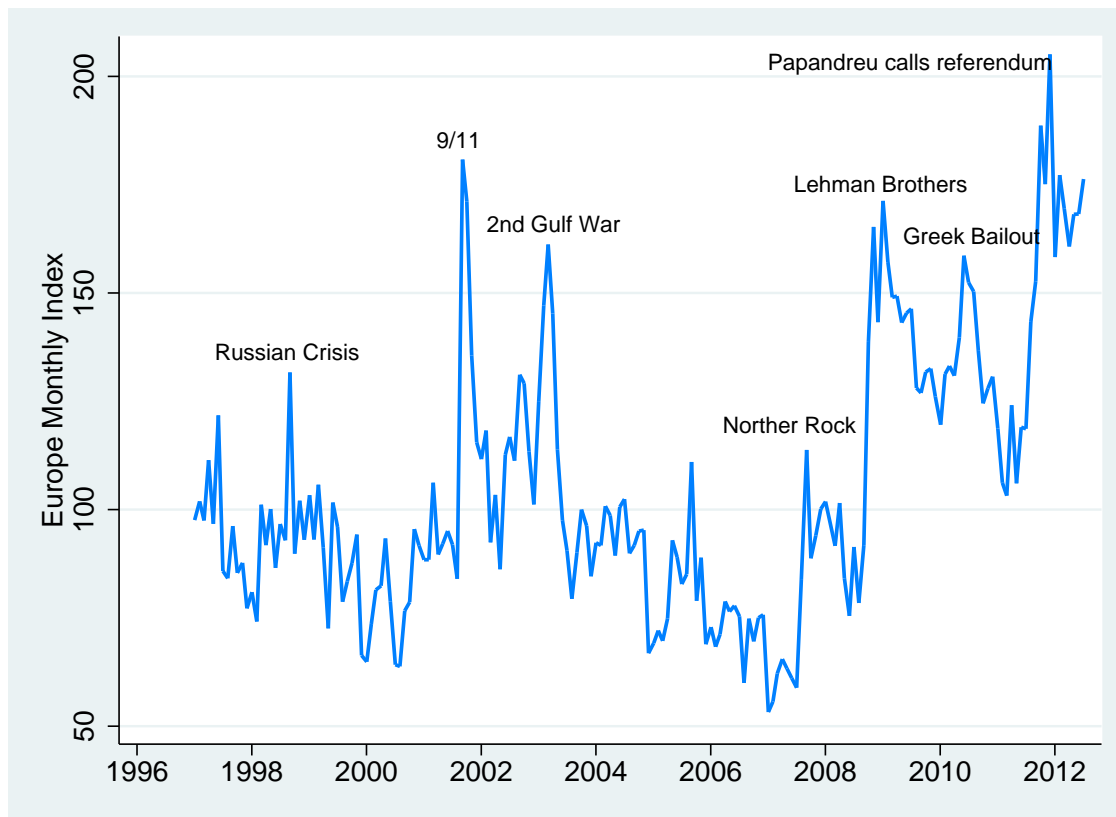
Let start with a speculator who has the opportunity to trade when  $\theta$  is at right of  $\bar{\theta}(p(t))$ : it is dominant for him to sell. Now consider a speculator slightly to the left of  $\bar{\theta}(p(t))$ , he will sell his asset holdings too. In fact, if he was observing a shock of size  $\bar{\theta}(p(t))$ , he was at most indifferent between buying or selling the asset, but now he knows that if  $\theta$  changes stochastically over time, small perturbations to the severity of the shock  $\theta$  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  $\theta$ . Given this path, speculators in  $A$  and  $B$  expect the same path of  $\theta_t$ . Suppose by contradiction that  $A$  and  $B$  were different, then the  $\theta$  that the speculator in  $B$  expects would at all times exceed the  $\theta$  that  $A$  expects by an amount equal to the initial difference in the  $\theta$ 's. Since the relative payoff to sell is increasing in  $\theta$ ,  $B$ '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. ■

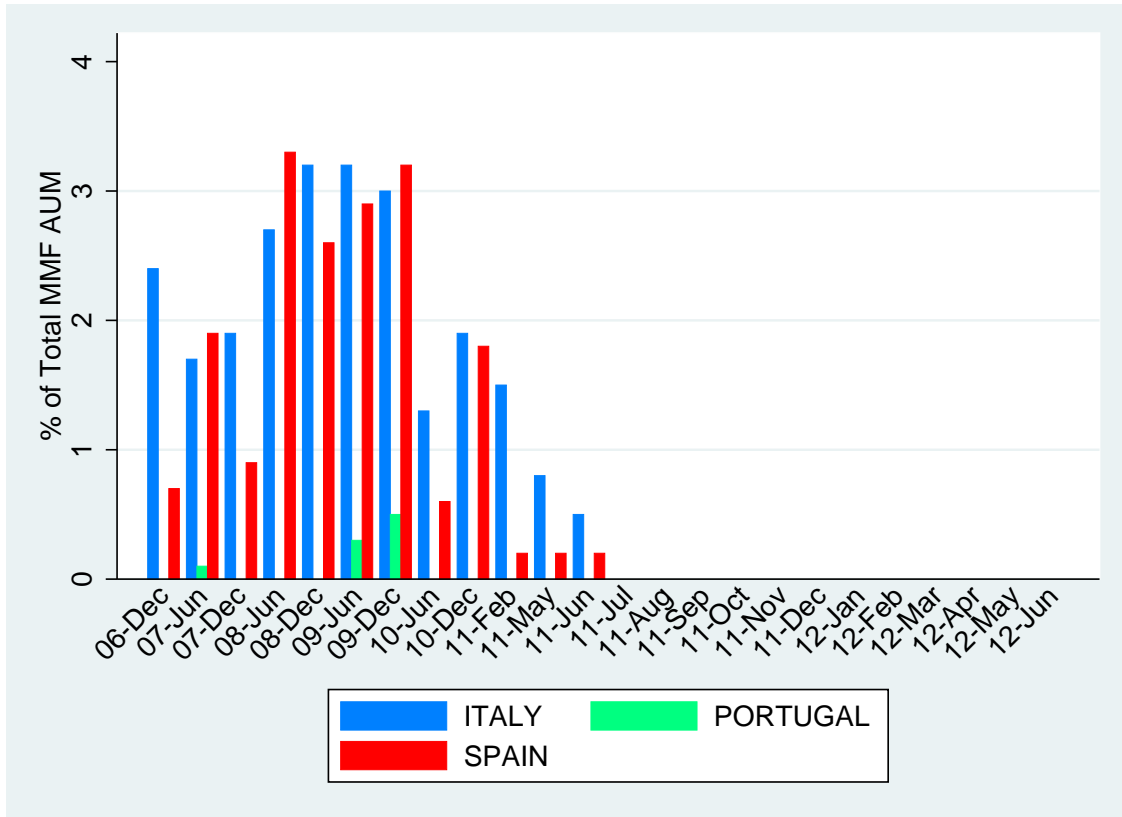
## 10 Appendix B- Evidence of Strategic Motive

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.

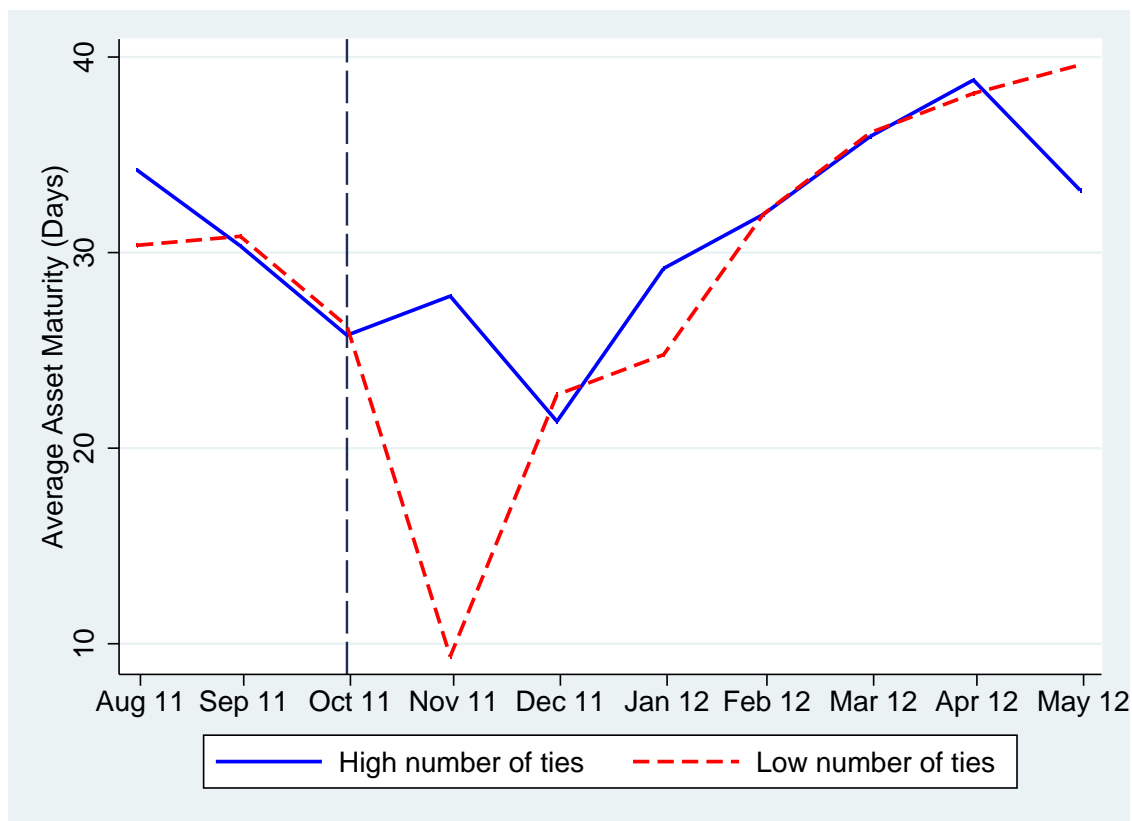
Figure 9: MMMFs exposure to the PIIGS



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).

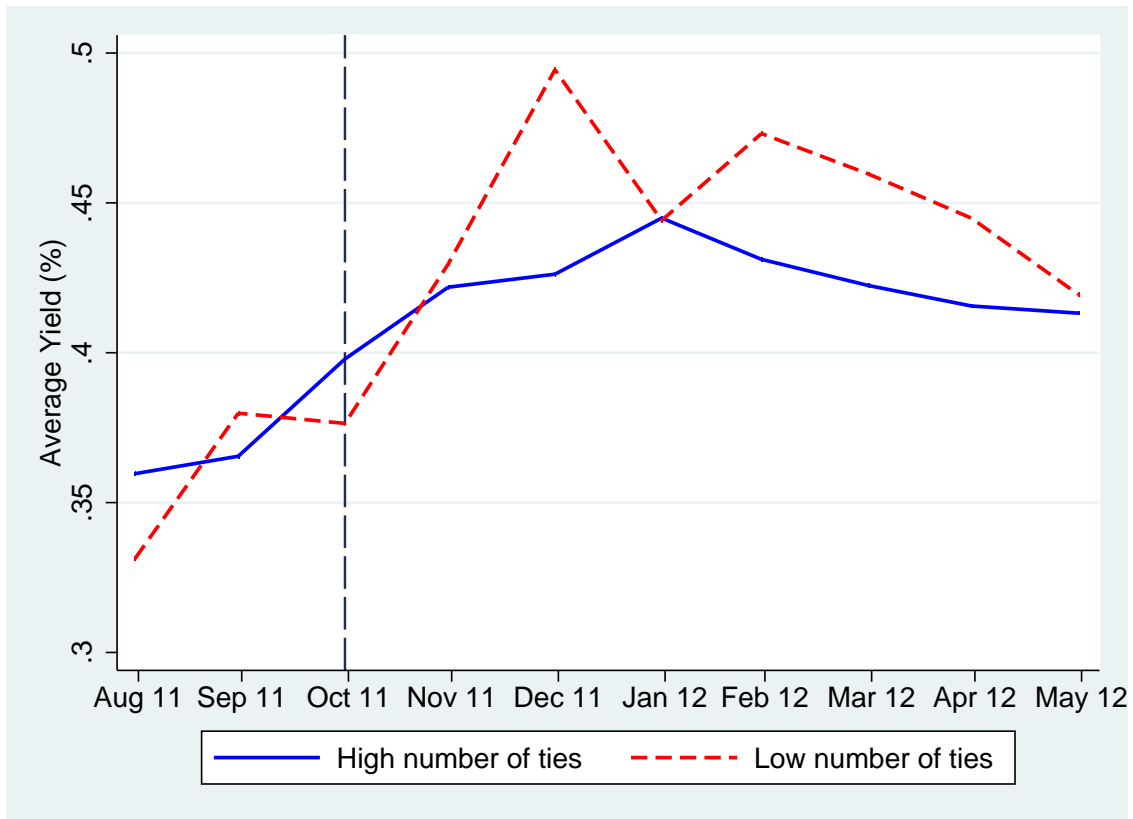


Figure 10: Average Asset Maturity



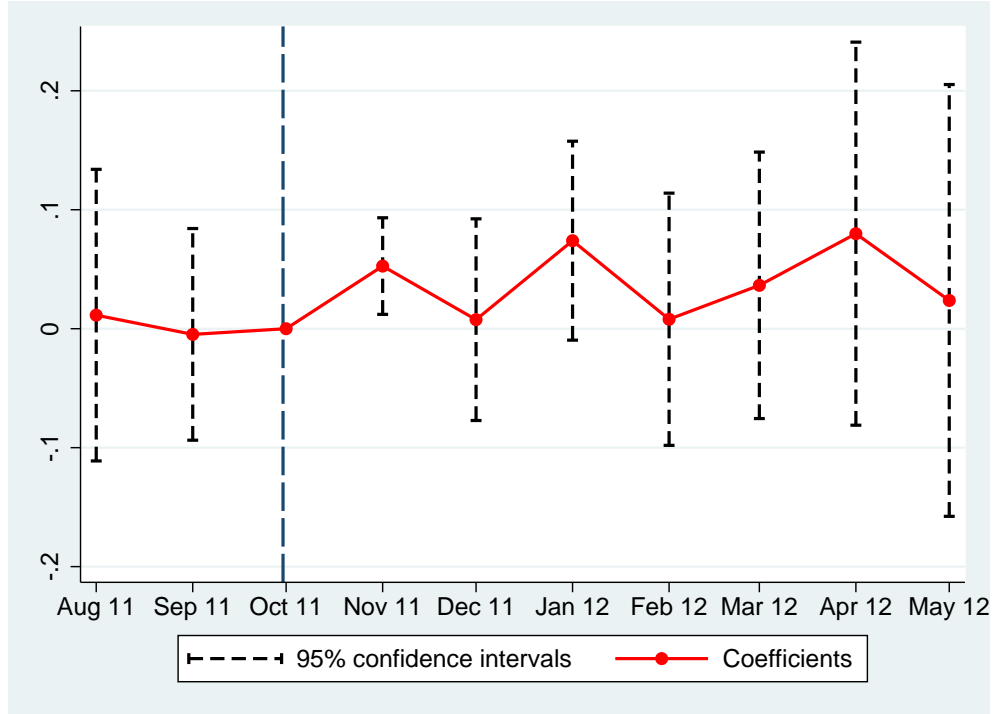
Notes: The panel above plots the average asset maturity issued by European institutions that have above (the blue continuous line) and below (the red dashed line) average number of borrowing relationships with MMFs for the period August 2011-May 2012. The vertical line identifies the post period after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

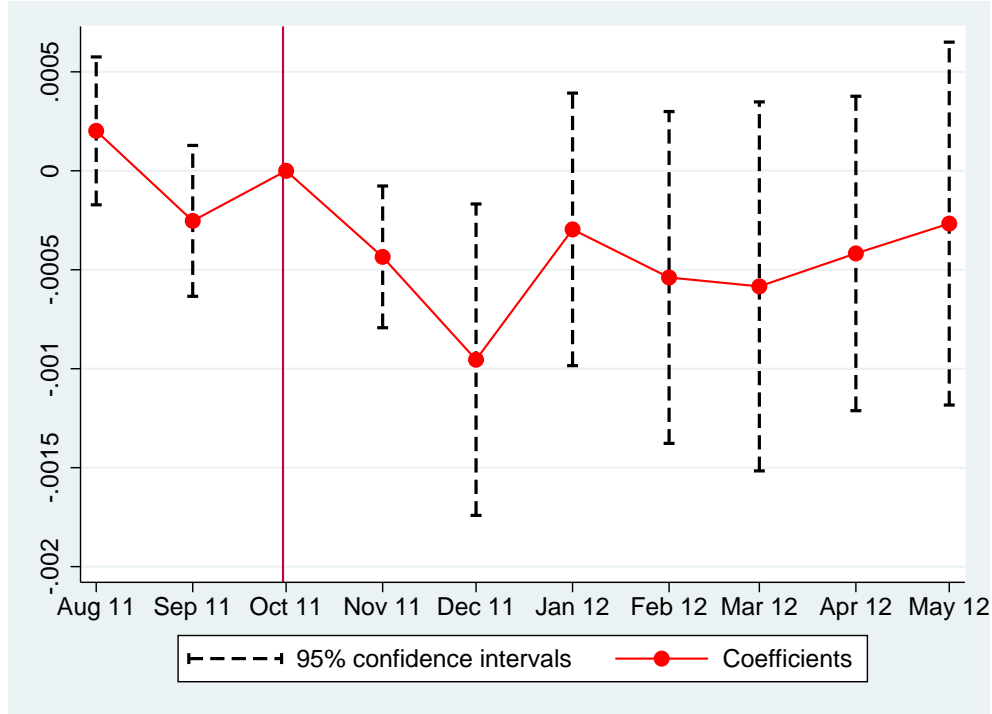
Figure 12: Event Study: Flight from Maturity



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.

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

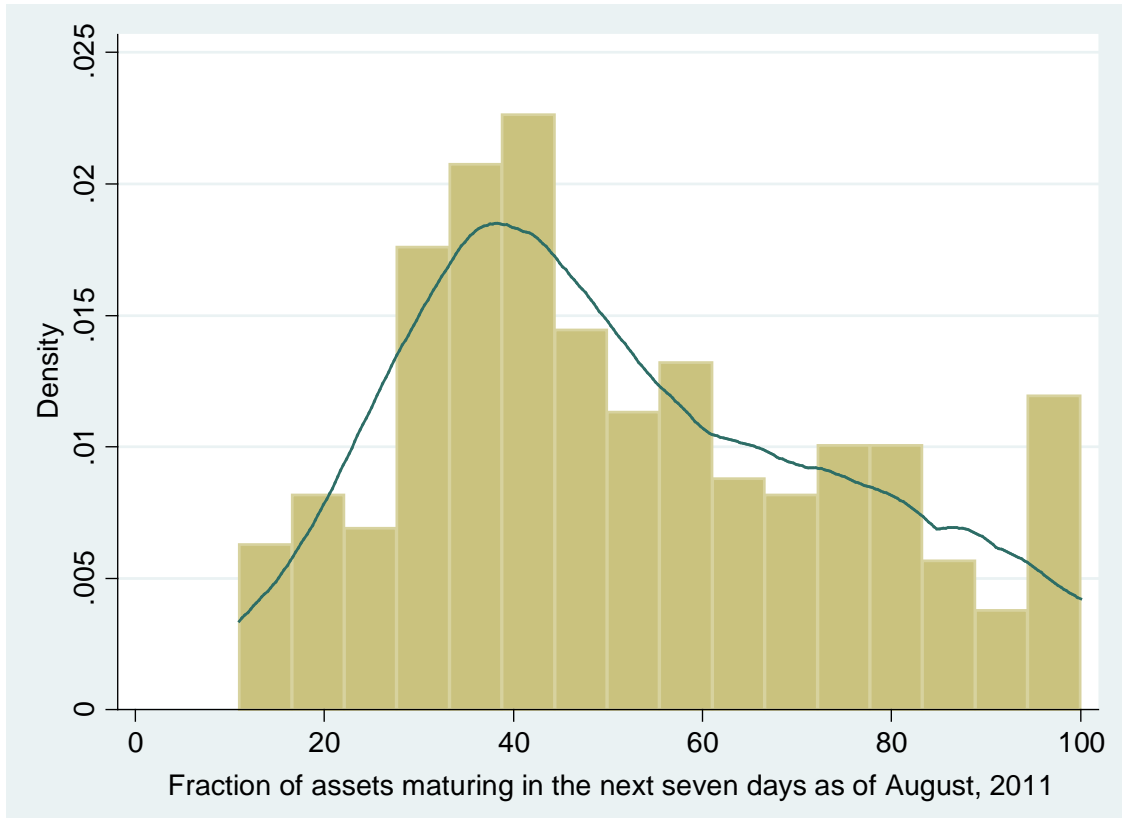
Figure 13: Event Study: Cost of Capital



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.

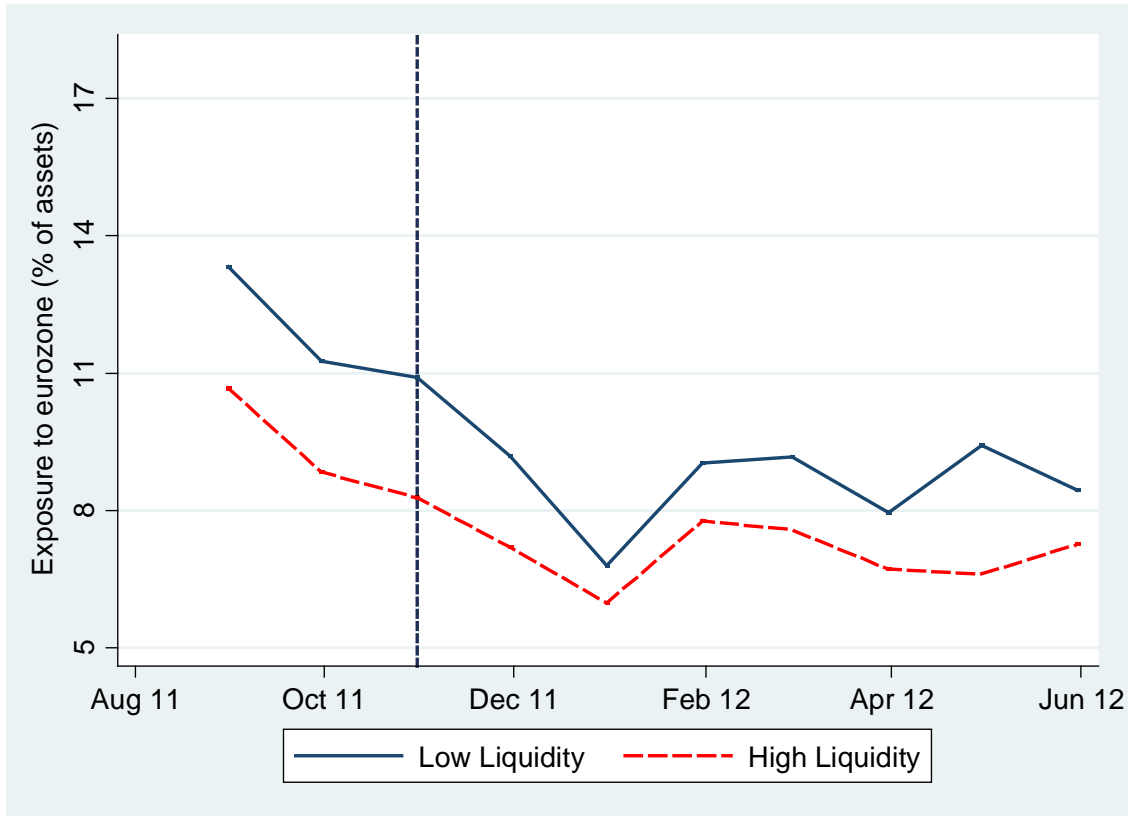
$$Issuer Yield_{g,t} = \sum_{\tau \neq t_0} \beta_{\tau} Issuer Ties_{g, Aug 11} \mathbf{1}_{(\tau=t)} + \gamma_t + \phi_g + \varepsilon_{g,t}$$

Figure 14: Kernel Distribution of MMMFs' Portfolio Liquidity



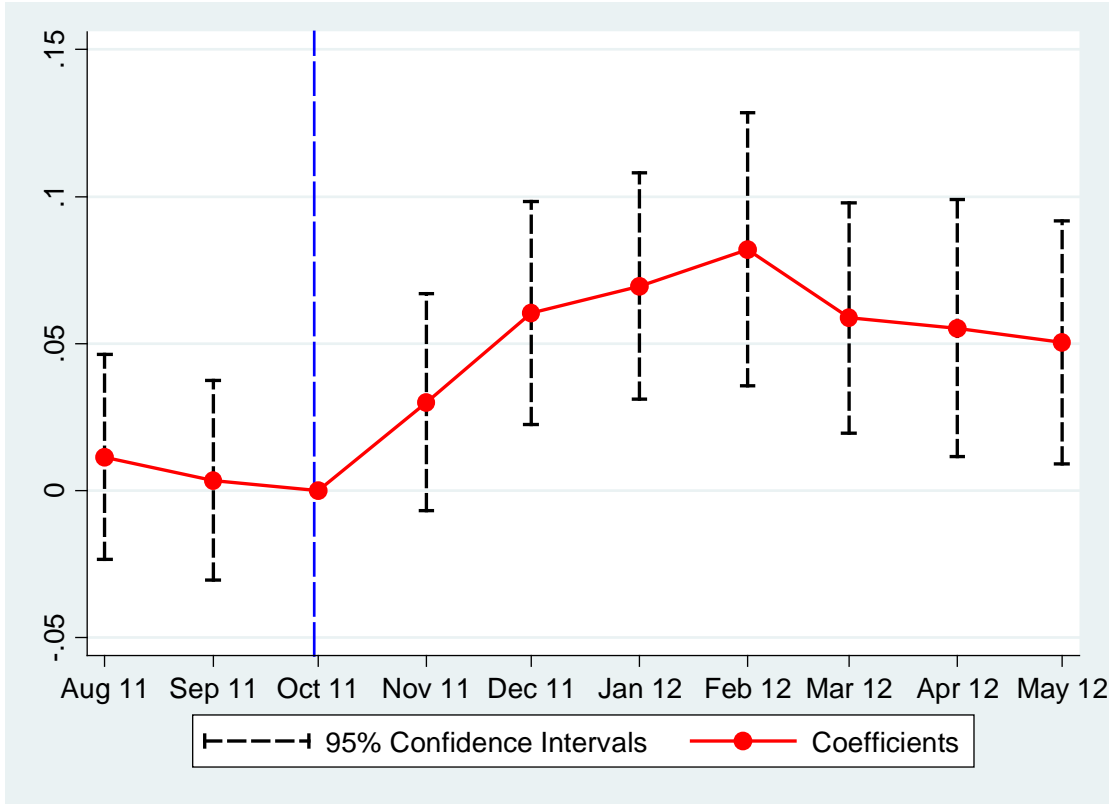
Notes: The panel above plots the kernel density of the fraction of assets maturing in the next seven days for all taxable funds in the period August 2011-May 2012.

Figure 15: MMMFs Exposure to the Eurozone



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

Figure 16: Event Study: Uncertainty Shock and Exposure to Eurozone



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

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

Table 1: Summary Statistics

	Mean	Median	SD	Min	Max
<b>Panel A: Fund Characteristics</b>					
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
<b>Panel B: Holdings information</b>					
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
<b>Panel C: Region of risk</b>					
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
<b>Panel D: Securities and Issuers Characteristics</b>					
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) $\Delta$ % AUM Invested	(2) $\Delta$ Amount Invested	(3) $\Delta$ % AUM Invested	(4) $\Delta$ Amount Invested
Number of Ties <sub>Aug 2011</sub> $\times$ Post indicator <sub>Oct 2011</sub>	0.00252*** (0.000706)	118,425** (58,415)		
Number of Ties <sub>Aug 2011</sub> $\times$ Post indicator <sub>Feb 2012</sub>			-0.00176*** (0.000604)	-100,312* (59,975)
Time fixed effects	✓	✓	✓	✓
Issuer fixed effects	✓	✓	✓	✓
Observations	13,719	13,719	10,237	10,237
R-squared	0.001	0.001	0.009	0.004

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

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

Table 4: The Effect of Issuer Riskiness

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

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

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

Table 5: Flight from Maturity

	(1)	(2)	(3)	(4)	(5)	(6)
Post indicator <i>Aug 2011</i>	-7.712*** (0.581)					
Post indicator <i>Feb 2012</i>				21.13*** (6.113)		
Number of Ties <sub><i>Aug 2011</i></sub>	-0.0491*** (0.00511)	-0.0479*** (0.00509)		0.166* (0.0893)	0.107*** (0.0379)	
Number of Ties <sub><i>Aug 2011</i></sub> × Post indicator <i>Oct 2011</i>	0.0117* (0.00668)	0.0126* (0.00666)	0.0534*** (0.00334)			
Number of Ties <sub><i>Aug 2011</i></sub> × Post indicator <i>Feb 2012</i>				-0.166* (0.0909)	-0.118*** (0.0381)	-0.0570*** (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 <i>Aug 2011</i>	0.140*** (0.00586)			
Number of Ties <sub>Aug 2011</sub>	0.000516*** (4.22e-05)		-0.000248*** (4.04e-05)	
Number of Ties <sub>Aug 2011</sub> × Post indicator <i>Oct 2011</i>	-0.000495*** (5.56e-05)	-0.000299*** (3.07e-05)		
Post indicator <i>Feb 2012</i>			-0.0505*** (0.00619)	
Number of Ties <sub>Aug 2011</sub> × Post indicator <i>Feb 2012</i>			0.000104* (5.86e-05)	0.000156*** (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) $\Delta$ % AUM Invested	(2) $\Delta$ % AUM Invested	(3) $\Delta$ % AUM Invested
Number of Ties <sub>Aug 2011</sub> $\times$ Post indicator <sub>Oct 2011</sub>	0.00682*** (0.00138)	0.00626*** (0.00166)	0.00621*** (0.00122)
Issuer CDS	-0.000457 (0.00126)	0.000680 (0.000730)	-0.000569 (0.00125)
Issuer CDS $\times$ Post indicator <sub>Oct 2011</sub>	-0.00259*** (0.000657)	-0.00303*** (0.000862)	-0.00233*** (0.000608)
Breaking the Buck	-14.97 (144.0)		-19.82 (161.0)
Breaking the Buck $\times$ Post indicator <sub>Oct 2011</sub>	28.51 (225.6)		36.30 (250.6)
Time fixed effects	✓	✓	✓
Issuer fixed effects	✓	✓	✓
Observations	4,768	4,093	4,553
R-squared	0.011	0.013	0.011

Notes: The dependent variable is the change in the fraction of assets invested in the issuer's securities by each fund, whereas in columns (2) and (4) it is the change in the dollar amount invested in the issuer's asset by each fund. Number of ties is the number of funds holding in August 2011 securities sold by the issuer. Post indicator is a dummy variable that equals 1 after October, 2011 or after February 2012. Issuer CDS is the time series of CDS prices extracted from Datastream. Breaking the Buck is the difference between \$1 and the fund NAV excluding the sponsor support. Column (2) restrict attention to funds that have a NAV  $\geq 1$ . 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 <sub>Aug 2011</sub> × Post indicator						
<i>Oct 2011</i>	0.0101*** (0.00235)	189,968 (156,176)	0.00403*** (0.00110)	396,440** (142,023)	0.00490** (0.00206)	0.00316*** (0.00106)
Issuer CDS	-0.00283 (0.00422)	-95,788 (211,069)	0.000770 (0.000582)	68,343 (101,918)		-0.000646 (0.00115)
Issuer CDS × Post indicator <i>Oct 2011</i>	-0.00334*** (0.00114)	-135,652 (147,553)	-0.00233*** (0.000670)	-279,005*** (44,177)		-0.00145*** (0.000500)
Fund Diversification <i>Aug 2011</i>					0.0229* (0.0125)	
Fund Diversification <i>Aug 2011</i> × Post indicator <i>Oct 2011</i>					-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)	(2)	(3)
	$\Delta$ % AUM Invested	$\Delta$ % AUM Invested	$\Delta$ % AUM Invested
Number of Ties <sub>Aug 2011</sub> $\times$ Post indicator <sub>Oct 2011</sub>	0.00609*** (0.00188)	0.00632*** (0.00224)	0.00736** (0.00282)
Average Yield Issuer	-0.0441 (0.632)	-0.159 (0.498)	-0.154 (0.433)
Average Yield Issuer $\times$ Post indicator <sub>Oct 2011</sub>		0.245 (0.462)	0.307 (0.414)
Average Maturity Issuer	0.00807 (0.00787)	0.00826 (0.00600)	0.00400 (0.00497)
Average Maturity Issuer $\times$ Post indicator <sub>Oct 2011</sub>		0.000464 (0.00566)	-0.000818 (0.00525)
Issuance Size			0 (0)
Issuance Size $\times$ Post indicator <sub>Oct 2011</sub>			-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.



## 11 Appendix C - MMFs Trading Strategies

Table 10: Impact of Uncertainty on MMFs Exposure to Euro Area

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

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

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

Table 11: Impact of Uncertainty on MMFs Exposure to Euro Area

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

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

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

Table 12: Changes in MMFs Portfolio Liquidity

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

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

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

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