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Costs and Benefits of Speculation

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Abstract

We quantify the effects of financial regulation in an equilibrium model with delegated portfolio management. Fund managers trade stocks and bonds in an order-driven market, subject to transaction taxes and constraints on short-selling and leverage. Results are obtained on the equilibrium properties of portfolio choice, trading activity, market quality and price dynamics under the different regulations. We find that short-sale restrictions reduce short-term volatility and long swings in asset prices, while transaction taxes do more harm than good.

Keywords: Financial regulation; portfolio management; market microstructure.

JEL classification: D53; G18; C63.

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1 Introduction

Since the onset of the financial crisis in 2007, policy makers around the world have been engaged in a fight against speculation. Temporary short-sale bans and other restrictions on leverage were imposed in more than 30 countries to restore financial stability, and there is growing support for the introduction of a financial transaction tax to discourage speculative trading. As part of the current push for tighter regulation these measures may soon be voted into law. Whether the benefits will outweigh the costs is an open question. The empirical evidence on the short-run effects of leverage constraints and transaction taxes is mostly negative but very little is known about the long-term consequences.

This paper analyzes the long-term equilibrium effects of regulatory reform in order-driven financial markets. We propose a modeling framework which integrates trading and asset management, and apply it to the issue of curbing speculation by means of leverage restrictions and taxes on financial transactions. We measure the impact of these regulations on market characteristics such as portfolio holdings, order flow, liquidity, cost of capital, price discovery, short-term volatility and long-term price dynamics. Quantitative results are obtained by comparing equilibria under different regulatory regimes to a benchmark that is calibrated to U.S. institutional details and stylized facts.

The model combines a general description of investor behavior with a detailed representation of the market microstructure. The real economy is modeled as an aggregate firm whose earnings are generated by a stochastic process with an unobservable business cycle component. The firm is financed with debt and equity. Stocks can be traded against bonds by submitting orders to an exchange which operates a continuous double auction. Short or leveraged long positions in the stock can be held subject to fulfillment of margin requirements, and transactions may be taxed. Brokers enforce compliance with margin-trade regulations. A clearinghouse takes on all counter-party risk.

Investors are modeled as fund managers who trade stocks and bonds on behalf of clients. Each fund's strategy is fixed throughout its lifetime, but competition from new entrants exerts pressure on low-performing funds by increasing their risk of client attrition.[1] The market for portfolio management services is modeled as a multiperiod tournament based on past performance. Brown, Harlow & Starks (1996) and Brown, Goetzmann & Park (2001) find that models of this type capture many empirical regularities associated with entry and exit of managed funds.

An equilibrium in our model is a set of trading strategies such that (a) no individual strategy can be systematically outperformed by some alternative trading strategy; and (b) the market is weak-form efficient. A genetic programming algorithm with tournament selection is applied to search for new strategies that outperform existing ones until the conditions for equilibrium are met. The outcome of this search is a set of heterogeneous strategies which are adapted to the institutional setting and geared towards survival. Agent heterogeneity is endogenous with respect to range as well as distribution, in contrast to heterogenous agent models where the range of behavioral variation is fixed ex ante. We find, however, that a substantial part of this heterogeneity can be represented by a small number of common investment styles which are robust to variations in the regulatory regime, although their relative importance differs between scenarios.

Four regulatory scenarios are considered: (i) A benchmark scenario, calibrated to the stylized facts of the S&P 500 index and current U.S. stock market regulations, where trade is subject to initial and maintenance margin requirements and no transaction tax is levied; (ii) a short-sale ban, corresponding to a permanent and global implementation of the ban of short sales that was imposed during the financial crisis; (iii) a ban of all leveraged trade (both short-selling and borrowing); and (iv) a tax of 10 basis points on the value of a transaction imposed on the buyers of equity as well as debt.

The benchmark scenario is characterized by high trading activity in terms of volume, order size and trade frequency, and low transaction costs measured by bid-ask spread and market impact. Almost half of all wealth is managed by funds that make long-term invest-

[1] Busse, Goyal & Wahal (2010) find that competition among U.S. equity funds is intense with attrition rates as high as 25% over a 3-year horizon.

ments in the market portfolio. The most active traders are leveraged funds with speculative trading strategies. On average, stocks trade at a 25% discount to their net present value, but this risk premium is strongly counter-cyclical. High risk premia during recessions are partly caused by short sellers betting on the possibility that bankruptcies in the real economy will clear their short positions at no cost. Such bear runs aggravate downturns and amplify long swings in asset prices, as measured by the mean stock price decline from a peak in an expansion to a trough in the next recession.

A tax on financial transactions has a strong negative impact on trading activity and liquidity. In addition to its direct effect on transaction costs, the tax has an indirect effect of roughly the same size due to wider spreads and greater market impact. Price discovery is less efficient, but volatility is slightly lower than in the benchmark scenario. Higher transaction costs lead to more long-term investment in the market portfolio, but the relatively high trading activity among leveraged funds persists. We find no evidence that the tax reduces long swings in asset prices.

A short-sale ban reduces trading activity to about half the benchmark level, but without a negative effect on transaction costs. Order book depth is reduced, but so are order sizes, and the net effect is a slight reduction in bid-ask spread and market impact. By curbing speculative bear runs, the short-sale ban reduces the depth of recessions and dampens long swings in asset prices. This yields a calmer market with slightly improved price efficiency, substantially lower volatility, and a 7% increase in stock prices.

A leverage ban reduces long swings further by curbing both bear runs and speculative bubbles. Volatility is on par with the short-sale ban scenario, but liquidity in terms of trade volume and market impact of large orders is worse. The order book is extremely shallow, but round-trip costs are only marginally higher than in the benchmark scenario because the leverage ban reduces the trade volume by 90% relative to the benchmark level.

This paper makes two main contributions, one practical and one methodological. First, our results provide guidance for policy makers by identifying the costs and benefits of speculation, and the trade-offs associated with the menu of regulatory options. We find that good market liquidity comes at the cost of high short-term volatility and enhanced long swings in asset prices, but that informational efficiency can be obtained without regard to the preferred mix of liquidity and market stability. Liquidity is best under the current regulatory regime, while market stability is best under a full leverage ban. A short-sale ban offers a compromise with the additional benefit of a lower cost of capital. A transaction tax entails costs but no significant benefits.

Second, we provide a versatile modeling framework capable of identifying equilibria in institutionally rich environments, and apply it to construct a model which integrates short-run trading activity with long-term asset management, as suggested by Parlour & Seppi (2008). The approach follows Alchian's (1950) idea of economic survival of the fittest and captures some of the features emphasized in Lo's (2004) formulation of the adaptive market hypothesis. The software implementation of the model and all data are publicly available through the authors' web sites.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 introduces the model and its calibration. Section 4 presents the results on the effects of short-sale and leverage bans as well as financial transaction taxes. Section 5 concludes.

2 Related literature

The literature on financial market regulation tends to focus on either portfolio choice or trading but rarely combines both. Papers focusing on portfolio choice typically abstract from the interplay between trading and market liquidity. This group includes most of the literature on leverage cycles and margin constraints, as well as research on transaction taxes in overlapping generations models. The second group focuses on the impact of short-sale constraints on the information content of prices. These papers usually abstract from portfolio management considerations. However, the interdependence between trading and portfolio management has proved to be relevant, for instance, in understanding the occurrence of short squeezes (Brunnermeier & Pedersen 2005); the collapse of hedge funds in 1998 (Brunnermeier & Pedersen 2009); and the relevance of position for traders' response to news (Lloyd-Davies & Canes 1978).

Theoretical studies find that short-sale constraints typically lead to less informative prices. Diamond & Verrecchia (1987) show that prices respond more slowly to new information, particularly if it is negative, when all traders face short-sale constraints. Hong & Stein (2003) find that short-sale constraints can contribute to market crashes, i.e., a fall in the price without arrival of new information. This happens when short-sale constrained investors with private information do not buy after a fall in the price. From their failure to act as support buyers the market learns that not all negative information is incorporated, leading to a further fall in the price.

Results on the effect of short-sale constraints on the price level are more ambiguous. Miller (1977) finds that short-sale constraints can lead to asset overvaluation when pessimistic traders are prevented from selling short. Scheinkman & Xiong (2003) show that this effect persists in a dynamic model with both rational and overconfident investors. In equilibrium, buyers are willing to pay more than their private valuation because of the embedded option to make a speculative profit by reselling the asset to a more optimistic investor. In contrast Diamond & Verrecchia (1987) do not find an upward bias to prices. Bai, Chang & Wang (2006) consider short-sale constraints that can affect either risk-sharing or informed trading. They demonstrate that prices can go up or down with a respective decrease or increase of volatility.

The asymmetric effect of short-sale bans on price efficiency is confirmed in the empirical study by Bris, Goetzmann & Zhu (2007). Other empirical papers find that short-sale bans reduce volatility (Chang, Cheng & Yu 2007) and increase stock prices (Chang, Cheng & Yu 2012). Both observations are confirmed by Chang, Luo & Ren (2012) who use a unique data set of Chinese stocks for which short-selling constraints were removed in 2010. They also find that a ban entails better price discovery with respect to positive news.

Empirical studies of the 2008 short-sale ban find significant negative effects on liquidity, price discovery and volatility, see, e.g., Battalio & Schultz (2011), Beber & Pagano (forth.), Boehmer, Jones & Zhang (2009), Boulton & Braga-Alves (2010), Kolasinksi, Reed & Thornock (2010), and Marsh & Payne (2012). Beber & Pagano find that the ban was largely ineffective in supporting stock prices in most countries except the U.S. This effect may in part have been due to the U.S. market's anticipation of the Troubled Asset Relief Program. However, Harris, Namvar & Phillips (2009) use a factor analytic approach to show that TARP did not contribute significantly to higher stock prices during the U.S. ban.

A case for active management of margin requirements to fight speculative bubbles was made by Robert Shiller after the burst of the dot-com bubble in 2000.[2] More recently, the G20 countries have taken steps to discourage excessive leverage. Among the tangible outcomes of these initiatives is the European Parliament's Legislative Resolution 'on the proposal for a regulation [...] on Short Selling and certain aspects of Credit Default Swaps' (COM/2010/0482). This resolution seeks to restrict short-selling with the aim of preventing speculative attacks against European sovereign debt instruments and financial institutions.

The destabilizing effects of leverage are well documented. Leverage can exacerbate asset price movements through several channels: directly affecting borrowing capacity (Kiyotaki & Moore 1997), pro-cyclical borrowing induced by counter-cyclical volatility (Adrian & Shin 2010), fire sales in illiquid markets during downturns (Shleifer & Vishny 1992, 2011), and forced closure of arbitrage fund managers' positions when mispricing becomes more severe (Shleifer & Vishny 1997). Similar mechanisms are present in our model: Short positions are increased when stock prices fall, volatility, bid-ask spread and market impact are all counter-cyclical, and losses on speculative positions increase the risk of client attrition.

Theoretical studies find that transaction taxes have negative effects on trade frequency and volume (Constantinides 1986, Kupiec 1996, Scheinkman & Xiong 2003). Kupiec (1996)

[2]'Margin Calls: Should the Fed Step In?,' Wall Street Journal, April 10, 2000.

finds that asset prices are reduced by the net present value of the effective tax and that volatility is increased. In contrast Constantinides (1986) and Scheinkman & Xiong (2003) find that the tax impacts neither price level nor volatility. Moreover, Vayanos (1998) shows in an overlapping generations model with several rounds of trade that taxation can increase prices as old agents are less reluctant to sell when transaction costs are high. None of these papers consider the market microstructure where trading costs can also increase as a result of wider spreads or a shallower book. In quote-driven markets the effect of a tax on prices and trading costs depends on the competition between market-makers and the degree of information asymmetry (Subrahmanyam 1998, Dupont & Lee 2007).

Empirical studies have found transaction taxes to reduce liquidity, increase the cost of capital, and impede price discovery without reducing volatility. Schwert & Seguin's (1993) survey provides a detailed account of the literature prior to 1993, and Matheson (2011) gives a more recent overview. Empirical evidence from UK data, where the stamp duty on stock purchases has been changed three times during 1974-1986, is provided in Bond, Hawkins & Klemm (2004), Jackson & O'Donnell (1985), and Saporta & Kan (1997). Umlauf (1993) studies Swedish data where transaction taxes were increased to 2% from 1% in 1986. Campbell & Froot (1994) provide a detailed account and also quantify the impact of the tax on investor behavior, migration of trade and use of non-taxed instruments such as derivatives.

The policy debate on the benefits of transaction taxes has a long history in economics. Keynes (1936) argued that excessive short-term trading by uninformed traders could lead to speculative bubbles and should be discouraged through transactions taxes. The proposal was revived by Tobin (1978) as a tax on foreign exchange to reduce short-term international capital mobility. Stiglitz (1989) and Summers & Summers (1989) lend their support to the tax as a means to discourage wasteful information gathering and prevent market crashes. Since then financial transaction taxes have received considerable support among academics, and European policy-makers have taken steps towards their implementation.[3]

[3]See, e.g., the Center for Economic and Policy Research's (CEPR) open letter 'Economists in Support of Financial Transaction Taxes' (December 3, 2009)—and Krugman's opinion piece 'Taxing the Speculators'

3 Model

The model represents fund managers who trade, on behalf of their clients, the debt and equity of an aggregate firm over an infinite time horizon. Trading takes place in a continuous order-driven market, subject to margin requirements and transaction taxes.

3.1 Market and investors

Financial securities. Stock and bonds are issued by one aggregate firm. The firm is represented by a stochastic earnings process which yields e_t per share per day $t = 1, 2, \ldots.$ The bond price is used as a numéraire and set to one. The price per share of stock is denoted p. On day t, there are $\mathcal{S}_t$ shares and $\mathcal{B}_t$ bonds outstanding. Debt per share is $d_t := \mathcal{B}_t/\mathcal{S}_t$. Each bond entitles its holder to a fixed overnight interest payment $r > 0$. Shareholders receive a dividend equal to the residual net income $e_t - rd_t$ per share.

Negative net income is associated with financial distress of firms in the real economy, leading to dilution of existing shareholders' equity through debt restructuring or bankruptcies. We abstract from the details by assuming that negative net income leads to interest payments that consist in part of a transfer of shares from shareholders to bondholders. For each bond, the aggregate firm pays e_t/d_t and the shareholders make up the shortfall by transferring $(r - e_t/d_t)/p_t$ shares to the bondholders. This procedure implies that bonds are risk-free, and that shareholders have limited liability.

We assume that the aggregate firm pursues a financial policy to keep debt per share constant at $d := d_0$. At the end of every trading day it issues new shares and bonds in proportions $1 : d$. Investors spend all of their income on the new issue by purchasing $e_t/(p_t + d)$ shares of issued stock for each share held, and investing their remaining income in new bonds. The number of shares and bonds bought is then $\mathcal{S}_t e_t/(p_t + d)$ and $\mathcal{S}_t e_t - p_t \mathcal{S}_t e_t/(p_t + d) = d\mathcal{S}_t e_t/(p_t + d)$, respectively. This leaves debt per share constant at d and

in the New York Times (November 26, 2009). Financial transaction taxes are recommended in the European Commission's 'Proposal for a Council Directive on a common system of financial transaction tax [...]' (COM/2011/594).

yields a total proceeds of $\mathcal{S}_t e_t$, equal to the total income of investors.

Earnings. The daily earnings per share of the aggregate firm are determined by a geometric Ornstein-Uhlenbeck process with time-varying mean. The specification of the EBIT-process follows Goldstein, Ju & Leland (2001) but adds an unobservable business cycle component as in Pástor & Veronesi (2003):

$$de_t/e_t = \eta^{s_t}\,(\mu^{s_t} - e_t)\,dt + \sigma\,dW_t, \tag{1}$$

where s_t is the state of the economy at time t. The economy is either in expansion ($s_t = 1$) or contraction ($s_t = 0$). Expected earnings are higher during expansions, $\mu^1 > \mu^0$, and the speed of mean reversion is higher in contractions, $\eta^0 > \eta^1$. The duration of the state of the economy is exponentially distributed with parameter ν^{s_t} where $\nu^1 > \nu^0$. Earnings exhibit short-term volatility σ and a medium-term trend $\eta^{s_t}(\mu^{s_t} - e_t)$.

The earnings process is observable, but the state of the economy is not. Given a Bayesian estimate of the probability P_t that the current state is 1, the net present value (NPV) of a share with current earnings e_t is

$$v(P_t, e_t) := (1 - P_t)\,v^0(e_t) + P_t\,v^1(e_t), \tag{2}$$

where $v^s(e_t)$ is the net present value of a share when the current state of the economy is s. Information about the earnings process is revealed at 100 equidistant points in time per day. These news events are a source of asymmetric information between traders who submit orders close to the arrival times of new information.

Order book. Shares are traded against bonds by submitting limit orders to an exchange which operates a continuous double auction. Each order is a commitment to buy or sell shares at the posted price up to the announced quantity. An order crossing the spread is a market order.[4] Market orders are executed at the best price offered by the current standing

[4]The term 'market order' is used here as short-hand for 'marketable limit order.'

limit orders. Partial execution against limit orders at different prices is possible, with any remaining quantity being added to the order book. At every point in time the order book is the collection of all non-executed orders. Limit orders are included in the book observing the usual price-time priority. A limit order remains in the order book until it is executed or the trader submits a new order which cancels any standing order by the same trader. The bid (ask) is the highest (lowest) price among all buy (sell) orders.

Margin trading. Investors can trade on margin by borrowing stocks or bonds to take on short or leveraged long positions in the stock. Short sales are covered, although we do not model individual lender-borrower contracts. We assume, however, that the supply of stock available for borrowing is limited to the current number of shares outstanding. Margin trading is managed by brokers, who will organize a stock loan for a short sale, or lend bonds for a leveraged long position, using the trader's portfolio as collateral. We assume that each trader has a margin account with a broker which encompasses the entire financial situation of the trader.[5]

A trader's assets consist of positive stock holdings valued at the bid, and claims on the broker and the aggregate firm. Claims on the broker are bonds deposited with the broker, and payments for any shares that have been sold in the past. Claims on the firm consist of accrued, but unsettled dividend and interest payments. Liabilities to the broker are loans to cover leveraged long positions in the stock, and stock loans valued at the ask.

We assume that the traders' claims on the broker yield overnight interest at the same rate as the bond. We also assume that margin loans (net debt to the broker) are charged at an additional 2.5% per annum.[6]

Margin requirements. Margin trading is subject to margin requirements which are set by regulatory authorities and brokers. An investor holding a portfolio with B_t bonds and S_t

[5]This is equivalent to assuming that the traders will honor their obligations to the broker as long as they are financially able to do so.

[6]In practice interest on margin loans comes in addition to the call money rate, which is the interest rate that banks charge to brokers for margin loans to their customers. We do not distinguish between short- and long-term interest rates and use 2.5% as a proxy for the broker's cost of providing a margin loan.

stocks meets the margin requirement M_t provided

$$\mathrm{M}_t|p_tS_t| \leq B_t + p_tS_t, \tag{3}$$

where p_t is the bid (ask) price for a trader who is long (short) in the stock, i.e., portfolios are marked-to-market. Initial margin requirements apply to new positions while existing positions are subject to lower maintenance requirements. In the U.S., the Federal Reserve Board (Regulation T) regulates initial margin requirements which have been set at 50% since 1974. Maintenance margin requirements are regulated by the Financial Industry Regulatory Authority (FINRA) and the stock exchanges. They currently require a margin of at least 25%, but most brokers have stricter house requirements, typically 30-35%. If a trader's equity ratio in a margin account falls below the initial margin requirement, the account becomes restricted and the broker is not allowed to increase lending. A trader with a restricted margin account can only place orders that will increase her equity ratio, i.e., buying (selling) stocks if short (leveraged long). We impose initial and maintenance margin requirements of 50% and 33%, respectively. Under a short-sale ban, leveraged long positions are allowed subject to fulfillment of these requirements. If all margin trade is banned, investors cannot be short in either stocks or bonds.

Circuit breakers and pre-trade risk management. Most exchanges use circuit breakers to halt trading in response to large intraday market-wide declines in security prices. After a halt, trading is usually restarted with a call auction. We simplify by restricting the price range of submitted limit orders to the current market price ±10%. Similar mechanisms are used by futures market operators such as CME. We also impose a maximal order size amounting to 1% of the total number of shares outstanding.

Transaction tax. A tax of 10 basis points on the value of a transaction can be levied on the buyer of a financial asset. The tax is paid by buyers of stock as well as bonds.

Clearinghouse. Settlement of trades and overnight payments of dividend and interest are handled by a clearinghouse. A portfolio (B_t, S_t) held at the end of a trading day receives the amount

$$r\,B_t + (e_t - rd)\,S_t - b_f L_t, \tag{4}$$

where $e_t - rd$ is the net income per share, r the overnight interest rate, b_f the broker fee, and L_t the trader's margin loan. We assume that a margin loan agreement must cover the trader's current leverage with the addition of any that would result from the execution of some standing limit order with positive or negative quantity Q_t. The effective margin loan is

$$L_t = -\min\{0,\ p_t S_t,\ p_t(S_t + Q_t),\ B_t,\ B_t - p_t Q_t\}.$$

The clearinghouse assumes all counter-party risk in return for receiving all broker fees for margin trades. It also honors any claims against bankrupt traders. An investor holding a portfolio with negative market value at the time of his arrival at the market is declared bankrupt and his holdings are transferred to the clearinghouse. Portfolios of investors who exit (enter) the market are also transferred to (from) the inventory of the clearinghouse. The clearinghouse reduces its net holdings of stocks and bonds at a rate of 1% per day through positive or negative transfers to investors at the end of each trading day. The amounts transferred are proportional to the net wealth of each investor. Clearinghouse transfers represent primary market transactions. By modeling bankruptcies and other large transactions as clearinghouse transfers, we avoid contaminating the order flow with transactions that are usually processed in the primary market.

Investors. There are finitely many investors, indexed $i = 1, ..., N$. Investors will also be referred to as 'traders,' 'funds' or 'fund managers,' depending on the context. Each investor has a strategy which determines her current limit order, i.e., a price-quantity pair, as a function of the information available at the time of order submission. Trading strategies are implemented as computer programs.[7] A trader's information comprises knowledge about the

[7]Each program consists of a list of at most 128 instructions, implemented in machine code. Each instruction specifies an operator and one or two operands. Operators consist of +, -, /, ×, *maximum, minimum,*

order book (bid, ask, and the quantities available at these prices), the net present value of a share, changes in the stock mid price and NPV during the last 24 hours, current portfolio holdings, and state of the margin account.

Order submission. A trading day is divided into N time periods. In each time period, a randomly selected trader arrives at the market. The broker first verifies whether the trader's current portfolio meets the maintenance margin requirement and, if not, enforces compliance by submitting a margin call. A margin call is modeled as a market order with a quantity that is large enough for the trader's post-trade portfolio to fulfill the maintenance margin ratio. If the trader receives no margin call, he can submit an order to the book. The order is derived from the trader's strategy, with real numbers being rounded to the nearest price tick and lot size. Positive and negative quantities are interpreted as buy and sell orders, respectively. A valid order is submitted as is and cancels any standing order by the trader.

A trader's strategy can produce invalid orders, i.e., orders that fail to comply with the margin restrictions, or orders that are meaningless. A margin violation occurs if execution of an order would cause the trader's margin account to become restricted, or if already restricted, would further reduce the trader's equity ratio. Meaningless orders are orders whose price or quantity is not a proper real number, e.g., as a result of division by zero. Invalid orders are dealt with by liquidating the leveraged part of a trader's portfolio, as a proxy for a broker's action to prevent potential losses on clients with erratic behavior.

Solution algorithm. The model is solved using a genetic programming algorithm with tournament selection (Koza 1992).[8] The model solution stage, which precedes the period where data are collected, consists of 15 million trading days. At the end of every trading day, there are four tournaments where underperforming fund managers are replaced by new

change sign, variable manipulations *swap, copy*, program-flow instructions, *if, goto*, and conditional statements $<$, $>$, $\leq$, $\geq$, $=$, $\neq$. Operands consist of 10 input variables, 4 temporary variables and 2^{13} numerical constants. When a program executes, the temporary variables are initialized to pre-defined values and the instructions are performed in order. The trader's quote (a price and a quantity) is determined by the values of the first two temporary variables after the program has executed.

[8]This approach is an extension of genetic algorithms that have been used to study models in financial economics that are not analytically tractable, see, e.g., Arifovic (1996), Lensberg & Schenk-Hoppé (2007), and Noe, Rebello & Wang (2003, 2006).

entrants who either follow investment strategies that performed well in the past or random modifications of those strategies.

In each tournament eight fund managers are randomly chosen from the population and ranked according to wealth under management. The strategies of the two fund managers with the lowest rank are replaced by copies of the strategies of the two with the highest rank. The copied strategies are then exposed to crossover and mutation.[9] The clearinghouse receives the holdings of terminated funds, and endows new funds with 20% of the average portfolio.

3.2 Calibration and data set

The benchmark scenario is calibrated with the current U.S. margin requirements and no financial transaction tax. Parameter values are either derived from empirical observations or chosen to give results consistent with historical averages and stylized facts. This is done by first calibrating the earnings process to capture those features that are related to business cycles, and the short-term variations that arise due to earnings surprises. We then simulate the model for a range of values of debt per share, and choose that which yields a mean equity ratio closest to the 60% long-run average of S&P 500 companies. Table 1 provides the main parameter values and details of their calibration. The parameter values of the calibrated model are retained in the other regulatory scenarios except for changes in margin requirements and taxation.

Convergence of the model is checked by testing for a structural break in the relationship between the risk premium and the NPV of the stock on data collected from the last 3 million days of the model solution stage. The risk premium is defined as $1 - p/\text{NPV}$. Table 2 shows no evidence of any structural break in these time series after 12 million trading days.

Weak-form market efficiency is tested using autocorrelations of daily log returns on data from the converged model. Figure 1 shows that the autocorrelations are small and generally

[9] A crossover swaps randomly selected sublists of instructions between two programs, and a mutation replaces one operation or operand in a program by a randomly generated one.

insignificant in all scenarios, except under a transaction tax. In the tax scenario, statistically significant autocorrelations below 2% are observed for lags up to 6 days. This yields a predictable price change from one day to the next which is less than 2 basis points (2% of 1% daily volatility), too small to compensate for the transaction tax. We conclude that the market is weakly efficient after 15 million trading days in all four scenarios.

The data set comprises time series of all investors' orders and portfolio holdings, the order book, and information about prices, earnings and NPV. It contains 200 independent time series over 10,000 trading days for each scenario, starting at day 15 million. Realizations of the earnings process differ between runs, but are identical across all regulatory scenarios for each run, which allows paired statistical tests on daily data relative to the benchmark. Table 3 contains summary statistics for key variables across the full data set of 8 million observations.

Table 3 shows that the NPV of the stock varies between 8.8 and 27, while the range of stock prices is much wider and includes the bounds 1 and 100 of the feasible set. A bound is hit when one side of the order book is empty. The number of such instances equals the number of missing observations for quantities at the bid and ask: 8 days with an empty buy book at the close, and 13 days with an empty sell book. These 21 instances occurred in the benchmark scenario of the model during 4 periods of extreme price fluctuations which lasted 16 days on average. There are large variations in the risk premium of the stock, and episodes with negative premia.

4 Results

This section presents quantitative results on the equilibrium effects of leverage constraints and transaction taxes using data on portfolio holdings, order flow, liquidity, cost of capital, price discovery, short-term volatility and long-term price dynamics.

4.1 Investor behavior

Specialization is a prerequisite for success in the market for portfolio management services. Fund managers therefore face a number of strategic choices. The most important ones concern investment style (product differentiation) and strategy implementation (trading and risk management). The complexity and variety in the investment styles of fund managers pose a challenge in forecasting the impact of regulatory reform. The 2008 short-sale ban, for instance, disrupted the business models of many financial firms that decried the measure as counterproductive to its aims. The Coalition of Private Investment Companies's letter to the SEC in 2011 provides an insightful account of the industry's sentiment and its opposition to current regulatory proposals.[10] In this section, we explore the variation in investor behavior across different regulatory scenarios. Our analysis shows that regulation has a profound impact on trading strategies, while portfolio holdings and other facets of style are affected to a lesser extent.

In markets with delegated fund management passive investment in the market portfolio offers two main advantages: Returns in line with the market average, and low transaction costs. Returns in line with the market average ensure low volatility of the fund manager's relative performance, which reduces the risk of client attrition. Table 4 shows that in all regulatory scenarios some 40-50% of total wealth is managed by funds that invest in the market portfolio, while wealth held in leveraged positions (short and long) amounts to less than 10%. This pattern is reversed with respect to trading activity. Table 5 shows that funds holding leveraged positions trade five to seven times more per dollar under management than the average fund, while those who hold the market portfolio trade less than half the average volume. Funds holding the market portfolio thus have the traits of passive investors, while those who hold leveraged positions are active portfolio managers.

The transaction tax raises the cost of active portfolio management and provides investors with additional incentives to pursue passive investment strategies. As a result, in this sce-

[10] http://www.sec.gov/comments/4-627/4627-139.pdf

nario more than 50% of total wealth is invested in the market portfolio. The effects of leverage restrictions on wealth invested in the market portfolio are not significant, but the market portfolio seems to attract more investors when a short-sale ban is extended to a full leverage ban.

Table 4 shows that a transaction tax does not discourage leverage, contrary to suggestions made by its proponents. Wealth in short positions actually increases, although by less than one percentage point, and wealth in leveraged long positions decreases by a similar amount. Consequently, wealth managed by all leveraged funds is barely changed relative to the 9% benchmark level. A short-sale ban increases wealth in leveraged long positions by about one half, but reduces overall leverage from 9% to 7.5%. Relative to the benchmark, a leverage ban generates a 60% increase in the wealth invested in portfolios that are long in one asset only. Although margin restrictions curb leveraged risk-taking, neither margin restrictions nor transaction taxes seem to dampen the investors' appetite for risk.

To explore the effects of regulation on investment styles, we collect data for individual traders on portfolio holdings, trading activity and sensitivity to information, and carry out a factor analysis for each scenario. The estimated models are structurally identical across scenarios and individual factors can be interpreted in terms of real-world trading styles. We examine the relative importance of these trading styles across scenarios, and find significant differences related to information acquisition and investment horizon.

Data for the factor analyses are obtained by randomly selecting one executed order for each scenario, run and day. This yields a total of $4 \times 200 \times 10{,}000 = 8$ million orders. For each order, we compute values for the 12 variables listed in Table 6. The first four variables represent trader size, trade volume relative to managed wealth, order type (limit or market order) and the distance of the trader's portfolio from the market portfolio. The remaining eight variables represent the sensitivity of the trader's decision function to information. For each information variable x_j, an indicator variable is set to 1 if a change in x_j alters the quoted price by at least one tick or the order quantity by at least one lot.[11] Vectors of indicator variables are divided by their sum (if positive) to obtain a measure of the extent to which the trade was based on selective information. Sensitivities to order book quantities are excluded to avoid multi-collinearity, and all variables are standardized by run to control for run level fixed effects.

To select the number of factors for the models, we compute eigenvalues from correlation matrices for the variables and include factors corresponding to eigenvalues greater than 1. Like other criteria for factor model selection, this one is vulnerable to sampling error. We deal with this problem by computing distributions for the eigenvalues with data from each of the 200 independent runs for each scenario. Figure 2 provides box plots of these distributions for the five largest eigenvalues. In each scenario, only the first three eigenvalues are consistently greater than 1.

Table 6 contains the results of estimating a three-factor model for each of the four scenarios. The factors are ordered by explained variance, except for the taxation case, where factors F_2 and F_3 are swapped to facilitate comparison with the other scenarios. White and black circles areas represent positive and negative factor loadings, respectively.

Factor F_2 distinguishes between two types of informed traders.[12] It assigns positive scores to traders who are sensitive to information on prices and net present values, and negative scores to traders who are sensitive to daily changes in those variables. Positive scores are representative of value traders, and negative scores typify news traders and arbitrageurs. Factor F_1 distinguishes between two types of uninformed traders. It scores positive for traders who are sensitive to the bid-ask spread and prefer limit to market orders. These characteristics are representative of market makers and other specialized liquidity suppliers. Negative scores are obtained by traders who pay attention to their portfolio position and the

[11] For example, sensitivity to the price level is measured by considering two parallel shifts of $\pm 1\%$ in the bid and ask, and sensitivity to the bid-ask spread is measured by widening and narrowing the spread by at most 4 ticks through mean preserving changes in the bid and ask while maintaining a minimum spread of 1 tick.

[12] Informed traders are traders who can form rational beliefs about asset mispricing. As a proxy we check whether a trader's order is sensitive to the stock price and NPV or to changes in both variables.

net present value of the stock, but who are insensitive to price information. These traders appear to be involved in carry trades or other cyclical strategies. Factor F_3 is a size factor which scores positive for large traders who hold positions close to the market portfolio, and negative for small traders who hold extreme positions and submit large orders relative to their equity.

We next examine whether the distribution of these styles varies across scenarios, Table 7. Styles are represented by proxy variables for liquidity suppliers, value traders, news traders and informed traders (news or value traders) on the raw data of Table 6.

Style distributions are qualitatively similar across scenarios except for a few notable differences relative to the base case: (i) Informed traders are underrepresented in the tax scenario; and (ii) the ratio of news traders to value traders is substantially higher in the tax scenario and lower in the scenario with a leverage ban. The first result supports Stiglitz's (1989) hypothesis that a transaction tax will reduce effort spent on information acquisition, but the second one disagrees with his conjecture that it could redirect investors' focus towards the long term and discourage short-term speculative trading. The results in Table 7 suggest that a full leverage ban would advance that goal, but that a short-sale ban would have the opposite effect.

4.2 Liquidity

Liquid markets offer investors the opportunity to trade large volumes at low cost whenever they want to trade. When liquidity dries up the consequences can be disastrous as evidenced by the fall of Long-Term Capital Management and other hedge funds in 1998 (Brunnermeier & Pedersen 2009). Transaction taxes generally reduce liquidity because trading becomes more costly. Sweden's painful experience with the effect of high transaction taxes in the late 1980s and early 1990s is a case in point. Now as then, proponents of the tax argue that low trading volume is a benefit as it discourages 'socially worthless activities' by clever and overpaid people.[13] There is also the, less commonly shared, view that frequent traders are net liquidity takers and therefore by curtailing their activities with a tax, liquidity may actually improve.

We analyze the net liquidity supply of different groups of investors, and provide results on order book properties and transaction costs. Table 8 contains information on net liquidity supply. Traders are classified by portfolio positions at the time of order submission, and net liquidity supply is measured as the difference between daily limit order and market order volume.[14] The executed volume of each order is attributed by equal parts to the trader's portfolio position at the time of the current and next order submission. In the base scenario, active investors demand liquidity and passive ones supply it. This pattern is enhanced when a transaction tax is imposed, contrary to arguments put forward by its proponents. Restriction of margin trade fundamentally alters the pattern of net liquidity supply. Table 8 reveals that under a short-sale ban the largest suppliers of liquidity are active traders who are constrained to holding all-bond portfolios. This effect disappears when the short-sale ban is extended to a full leverage ban because it hurts the customer base of market makers by eliminating all leveraged speculation.

Table 9 contains results on market liquidity measured by the bid-ask spread, market impact, order book depth and trading activity. The market impact of a buy (sell) order is the absolute difference between the current ask (bid) and the volume-weighted execution price. Endogenous market impact is computed across all executed orders, and order book depth is the market impact of a large order (0.2% of the benchmark trade volume), computed from the state of the book at the close of every trading day.

The base scenario is characterized by high liquidity with a low quoted spread of about 10 basis points and an endogenous market impact of only 1 basis point. The effects of the

[13] See Section 2.1.1 in Campbell & Froot (1994) for more details on these comments and the Swedish experience.

[14] For every order that is executed in full or part, the quantity that is executed against standing limit orders is classified as a market order, and any quantity that is executed against incoming market orders is classified as a limit order.

regulatory scenarios on the quoted bid-ask spread and endogenous market impact are small, except in the tax scenario where the spread is twice as high as in the benchmark scenario and market impact is five times larger. The effects on order book depth are more pronounced. A short-sale ban increases the market impact of the large order by 60%, and in the leverage ban and tax scenarios, the market impact is about four times larger.

Trade frequency, order size and trade volume are highest in the base scenario, Table 9. A short-sale ban reduces trade volume to about 50% of the benchmark level, and a leverage ban cuts it down to 10%. The transaction tax, despite being only 10 basis points, reduces the trade volume to 20% of the benchmark level. Differences in trade volumes are mainly due to differences in order sizes, except in the leverage ban scenario where a small order size is accompanied by a very low trade frequency.

The net effects of differences in liquidity on trading costs are shown in Table 9. Round-trip cost is the average cost incurred by a trader who uses market orders to open and close a position. It amounts to two times the 10 basis point tax plus the effective spread (bid-ask spread plus two times the average market impact). Relative to the base scenario, a short-sale ban reduces the round-trip cost by a marginal amount, while a leverage ban leads to a moderate increase. In contrast, the transaction tax increases the round-trip cost from 12 to 51 bp, of which 20 bp are directly related to the tax. The remaining 19 bp are due to a higher effective spread. This implies that 97.5% of the transaction tax falls on the liquidity takers. To see this, consider a round-trip involving an impatient trader and a market maker. Their transactions generate a tax bill of 20 bp to each party. In addition, the trader pays the market maker 19 bp as a result of the increased effective spread. This amount almost covers the tax bill of the market maker, except for a 1 bp reduction in profits.

The negative impact of the short-sale ban on trade volume and trading activity are consistent with the empirical evidence from the 2008 short-sale ban. However, the dramatic increase in the transaction costs of banned stocks reported by Boehmer et al. (2009) is not observed as an equilibrium effect in the model. This suggests that some of the empirical results on short-sale bans may be due to short-run effects which are not equilibrium phenomena.

The 2008 U.S. short-sale ban differs from the ban considered in our model in three main respects: (1) The ban was an emergency action taken in response to a severe decline in the market values of financial stocks; (2) the announcement marked an unexpected and temporary shift in the regulatory regime; and (3) during the 15 trading days the ban was imposed, prices of banned stocks continued to fall along with the overall market.

To assess the short-term effects of a temporary short-sale ban, we carried out a controlled experiment in a similar market situation within our modeling framework. From each simulation run, a period of market distress is selected that resembles the situation of the 2008 short-sale ban. This is done by choosing a period of 1 year and 15 days from each run of the base case as follows: For all periods, percentage declines in NPV over the first year and the subsequent 15 days are calculated separately, and the period with the largest product of the two percentage declines is selected. The last 15 days become the intra-ban period for the experiment. Data are collected from 200 runs on time paths for the earnings process identical to those of the base case, but with a temporary short-sale ban in place during each intra-ban period.

During the simulated 15-day ban, percentage volume-weighted spreads and endogenous market impact increase by 90% and 146% relative to the base case, while trade volume and the number of trades decrease by 22% and 18%, respectively. On day 15 of the ban, the stock price is up 9.4% relative to the base case. This is in line with the findings of Harris et al. (2009), who estimate a 10-12% price increase during the 2008 ban. Differences in stock prices and trading activity between the two scenarios increase throughout the temporary ban, but systematic differences in spreads and market impact disappear halfway through the ban. These findings suggest that lower trading activity is a permanent effect of a short-sale ban, while higher transaction costs are a temporary phenomenon associated with an unexpected change in the regulatory regime.

4.3 Market dynamics and the business cycle

The effect of regulation on long-term market movements is influenced by the governance structures in the portfolio management industry. Under delegated fund management, the principal-agent relationship between investors and fund managers relies on past performance as a proxy for unobservable skill, see e.g., Shleifer & Vishny (1997). This will induce short-sellers to increase their positions during downturns and decrease them during upturns, as observed by Lamont & Stein (2004). Short-sale bans could therefore benefit long-term market stability. In contrast, transaction taxes impact the order flow by raising the cost of trading, but have no direct effect on the cost of portfolio holdings. Their effect on long swings in asset prices is therefore less clear.

We find that leverage restrictions dampen long swings in asset prices by preventing bear runs during recessions, while a transaction tax has no effect. The peak-to-trough variable in Table 10 measures the amplitude of price movements over business cycles as the mean percentage decline in the stock price from a peak in an expansion to the trough in the subsequent recession. In the benchmark scenario, the mean peak-to-trough decline across 687 business cycles is 43.1%. Both types of leverage restrictions have a dampening effect on long-term price movements. A short-sale ban reduces the mean decline by 3.5 percentage points to 39.6%, and a leverage ban reduces it by 4.8 percentage points to 38.3%. A transaction tax, on the other hand, has no significant effect.

Second, leverage restrictions dampen long swings by supporting stock prices during recessions. Variables 'High' and 'Low' in Table 10 are the means of maximal and minimal stock prices across 200 40-year periods, and 'Range' is the difference between 'High' and 'Low.' While the high mean does not differ significantly across scenarios, the low mean is 15% higher in the two scenarios with a short-sale ban. The range is narrower under a full leverage ban, but is not significantly different in the other three scenarios. Differences in long swings reflect differences in the cyclicality of risk premia, Table 11. The risk premium on the stock moves counter-cyclically in all scenarios, but less so in the two scenarios with a short-sale ban.

Third, leverage restrictions support stock prices during recessions by eliminating downward price pressure from counter-cyclical short-selling. Table 11 shows that short interest is strongly counter-cyclical in the base and tax scenarios, with short positions increasing during downturns and decreasing during upturns. This is consistent with Lamont & Stein's (2004) observation that short interest moved counter-cyclically during the dot-com bubble.

Fourth, counter-cyclical short-selling is a consequence of delegated fund management, as predicted by Shleifer & Vishny (1997). Short sellers experience capital losses during upturns, and negative profits during booms when dividends are high. Their poor performance leads to a further reduction of wealth under management as clients withdraw funds. In downturns, capital gains are positive, and short sellers continue to perform well throughout the recession when dividends are consistently low. The good performance leads to an inflow of funds to short sellers which, in turn, allows them to take on larger positions.

In recessions, a short position is effectively a bet on high rates of bankruptcies among companies in the real economy. A short position generates a positive cash flow at the time of sale and, if the company is bankrupt, clears the short position at no cost. Leveraged long positions are different because borrowed bonds have to be repaid in full. Consequently, the incentives to hold leveraged long positions during booms are weaker than the incentives to hold short positions during busts. This difference in incentives explains the differences in cyclicality between short interest and long leverage in the base and tax scenarios of Table 11.

We conclude that leverage restrictions dampen long swings in asset prices by preventing bear runs caused by short sellers who speculate on financial distress of companies in the real economy. The transaction tax has no beneficial effect on long term price swings because it does not alter the incentives to hold leveraged positions.

4.4 Pricing and price discovery

This section is concerned with the effect of regulation on the level and information content of stock prices. From a macroeconomic perspective, higher stock prices reduce the cost of capital which promotes growth. Consequently, regulatory reform can improve welfare if it increases stock prices by reducing price fluctuations or by increasing the demand for stocks in other ways. On the micro level, efficient capital allocation relies on informationally efficient prices. Measuring the effect of regulation on price discovery, however, is a non-trivial task as fundamental values are usually unknown. Even when this is not the case, regulatory reforms may have confounding effects on price dynamics. Such effects can arise through changes in trading patterns when a short-sale ban is introduced, as suggested by the Wall Street wisdom that short-selling is good, rather than bad news as current sell pressure means future buy pressure.

We find that stock prices are highest under the short-sale ban and lowest in the base and tax scenarios, Table 12. The major part of these differences can be accounted for by volatility which is highest in the base scenario, slightly lower in the tax scenario, and much lower in the two scenarios with leverage restrictions. Lower volatility under the short-sale ban is in line with the empirical findings of Chang, Cheng & Yu (2012). However, while a short-sale ban increases the equilibrium price level by 7% in our model, a full leverage ban increases it by only 5%, despite lower volatility in the leverage ban scenario. We attribute the high stock price in the short-sale ban scenario to Miller's (1977) result on overvaluation in markets with diverging opinions and short-sale constraints.

Empirical studies show that transaction taxes lower asset prices (Bond et al. 2004, Schwert & Seguin 1993). In our model, the tax has no effect on prices, because it is applied to both assets. This observation lends support to a point made by the proponents of a transaction tax. If the tax is introduced, it should be global and uniform to cover all assets classes. Otherwise distortions may occur and the cost of capital is raised for issuers of taxed versus non-taxed assets.

Price reactions to news can be measured by considering the impact of actual news events, e.g., Vega (2006) or the amount of idiosyncratic risk reflected in stock prices, as suggested by Mørck, Yeung & Yu (2000). We combine the two approaches by applying the statistical measures of Bris et al. (2007) to actual news events. The efficiency of the price discovery process is measured as the R^2 in regressions of daily log stock returns on daily log innovations to NPV. To test for asymmetric price efficiency with respect to good and bad news, we compute upside (downside) R^2 in the same way for days with an increasing (decreasing) NPV. R^2 and the difference between downside and upside R^2 are reported in Table 12.

Price efficiency is generally high, with an R^2 of 87% in the benchmark scenario. It is worst under a transaction tax (83%), and best in the two scenarios with leverage restrictions (94%). Inferior price discovery in the tax scenario is due in part to higher transaction costs which generate larger hysteresis in the traders' response to information, as predicted by Constantinides (1986). Superior price discovery under the short-sale ban is at odds with the empirical findings of Bris et al. (2007), but consistent with Chang, Cheng & Yu (2012) and Chang, Luo & Ren (2012). Their data source is similar to ours in the sense that it comes close to being a controlled experiment.

Downside-minus-upside R^2 is positive across all scenarios, indicating that the markets digest bad news more efficiently than good news. Empirical studies based on earnings surprises (Vega 2006) find the same asymmetric effect, while studies based on idiosyncratic risk (Bris et al. 2007) find the opposite. Downside-minus-upside R^2 is smallest in the short-sale ban scenario. This is consistent with Diamond & Verrecchia's (1987) prediction that short-sale restrictions can impede price discovery in response to bad news by preventing short sellers from acting on private information. However, downside-minus-upside R^2 is only slightly higher under a full leverage ban, which suggests that additional effects are present.

We find that price discovery is adversely affected by bear runs (Section 4.3) and short squeezes.[15] Table 13 provides details on the behavior of margin traders during extreme

[15] Surges in stock prices caused by short squeezes are not uncommon. An illustrative example is provided in the Wall Street Journal, 'The Jury's In: Yelp's Surge Is a 'Short Squeeze',' August 29, 2012. Short sellers'

events, defined for each run as the 5-day period which maximizes the absolute log return on the stock. For each extreme event, we collect information about changes in the log stock price Δp, short interest ΔSI, and long leverage ΔLL. We also compute net margin trade $\Delta(LL - SI)$. All variables are normalized by their respective standard deviations computed by run on the full samples. The table contains conditional means and medians for each variable during crashes ($\Delta p < 0$) and bubbles ($\Delta p > 0$).

We first observe that that bubbles are relatively more frequent when short-selling is allowed. The ratio of bubbles to crashes is 2:3 in the base and tax scenarios and only 2:7 in the scenario with a short-sale ban. When short-selling is allowed, crashes and bubbles are associated with destabilizing bear runs and short squeezes, respectively. Short traders sell stock at a mean rate of 5.5 standard deviations during crashes and buy twice as much during bubbles. Traders with leveraged long positions act as contrarians, but their reaction is less extreme and more symmetric. Asymmetric margin trade is partly due to forced liquidations triggered by margin calls. In the base scenario, net margin trade is destabilizing and highly asymmetric at mean rates of 9 and -2.5 standard deviations during bubbles and crashes, respectively. In the tax scenario, the pattern is the same, but more pronounced. Under the short-sale ban, net margin trade is stabilizing and relatively symmetric at mean rates of about ± 4 standard deviations. Stock price movements during extreme events reflect differences in margin trade activity. During crashes, mean absolute returns do not differ significantly across scenarios. During bubbles, however, mean absolute returns are significantly higher in the scenarios where short-selling is allowed.

In the base and tax scenarios, the destabilizing effect of margin trade distorts the association of returns with innovations to NPV, and the asymmetric effect blurs the relationship between returns and positive innovations to NPV. The former leads to higher kurtosis and lower price efficiency in terms of R^2, and the latter to less negative skewness[16] and higher

predicament after a sudden price increase of 25% was cogently summarized by the co-head of trading at First New York Securities, Seth Setrakian, who is quoted “The shorts got caught with their pants down today, plain and simple.”

[16] Absent any asymmetric effects of trading, daily stock returns will display negative skewness because the

downside-minus-upside R^2 (Table 12).

To quantify the effect of the short-sale ban on the price efficiency measure during extreme events, we computed downside R^2 and upside R^2 after removing the 10 most extreme events from each run in the base and short-sale ban scenarios. Downside and upside R^2 increase in both scenarios, but the effect is one order of magnitude larger in the base case. In both scenarios, upside R^2 increases three times more than downside R^2. As a result, the difference in downside-minus-upside R^2 is reduced from 0.029 (Table 12) to 0.016. This implies that our estimate of the negative effect of the short-sale ban on price discovery in response to bad news is biased upwards by more than 80%. More generally, this analysis shows that regulatory reforms can have spurious effects on standard measures of price discovery,[17] and that these effects can sometimes be identified by examining differences in price dynamics during extreme events.

5 Conclusion

Financial stability is high on the agenda of politicians and regulators. Several measures have been proposed to deal with the recent crises, but quantitative knowledge about their long-term implications is scarce. Our paper attempts to fill this gap by introducing a new methodology to quantify the effects of regulatory reform in an equilibrium model with market microstructure. We apply this methodology to measure the effects of leverage restrictions and financial transaction taxes on market quality and financial stability. The approach enables a detailed analysis of the dynamic equilibrium of portfolio choice, trading activity, market quality and price dynamics under the different regulatory measures.

We find that a short-sale ban reduces both short-term volatility and long swings in asset prices which positively impacts price discovery and lowers the cost of capital. There is no adverse effect on transaction costs but liquidity is worse in terms of trade volume and order

skewness of daily innovations to NPV is negative at -0.18. Negative skewness in NPV is due to negative skewness in the Bayesian state probability, which has a median close to 1 and a fat left tail (Table 1).

[17] A similar point is made by Chang, Cheng & Yu (2012).

book depth. A leverage ban enhances the positive effects of the short-sale ban on market stability, but liquidity is very poor, and the cost of capital is higher. A financial transaction tax has a negative impact on liquidity and price discovery, but no significant effect on long swings in asset prices. While most studies of short-sale bans have focused on their ability to limit extreme declines in asset prices, our findings suggest that their ability to limit extreme price increases can be as important for short-run market stability.

Our analysis suggests some new hypotheses for empirical investigation: (1) Introduction of a short-sale ban has a permanent effect on stock prices and trading activity, but only a temporary effect on transaction costs; and (2) Evidence of inferior price discovery related to negative information about stocks subject to a short-sale ban can be accounted for by asymmetric price dynamics during extreme events.

The model can be extended in several directions to address further open issues. The effect of regulatory discrimination between asset classes can be explored by introducing cash as a medium of exchange and trading different assets against cash on separate order books. Other regulatory measures, such as uptick rules, can be studied in the present version of the model, and circuit breakers can be analyzed by adding a call auction mechanism. This approach can also be used to guide decisions on the choice between continuous trading and repeated call auctions in markets for illiquid assets.

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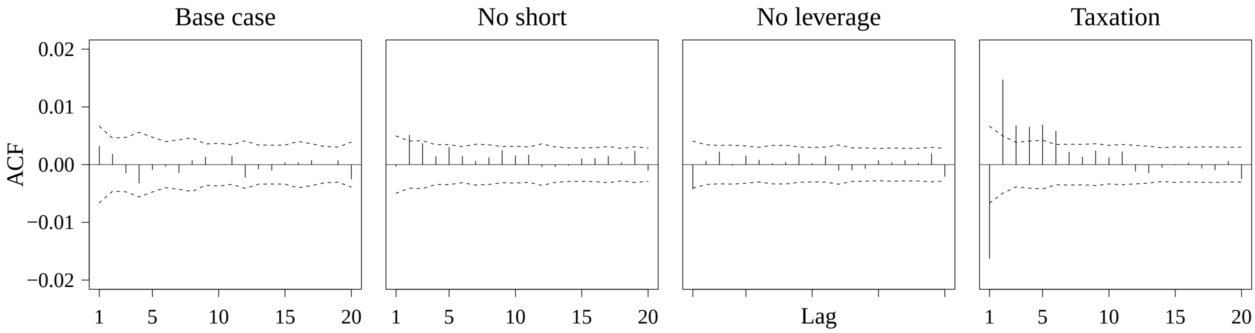

Figure 1: Autocorrelations in daily log returns. For each scenario, data are collected from 200 model runs over 10,000 trading days. The mean autocorrelation functions are computed across those 200 runs. The dashed lines connect confidence intervals of ± 2 standard errors computed at each lag.

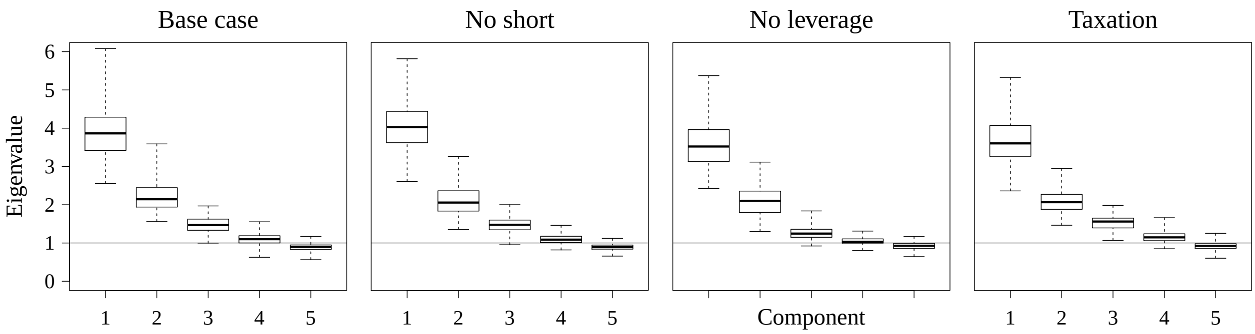

Figure 2: Eigenvalues for factor model selection. For each scenario and run, we compute the 12-dimensional correlation matrix and its eigenvalues from a random sample of 10,000 individual orders. For each scenario, the box plots show the range; the first and third quartiles; and the median of the 5 largest eigenvalues across the 200 runs of that scenario.

Table 1: Values of key model parameters.

Number of traders	$N = 20{,}000$	Sufficiently large population to sustain a competitive market.
Initial shares per trader	$S_0^i = 50{,}000$	Net supplies of shares and bonds are chosen to obtain a mean equity ratio close to the average across S&P 500 companies (about 60%).
Initial bonds per trader	$B_0^i = 500{,}000$	
Mean regime durations $1/\nu^s$	2 resp. 7 years	Calibrated to business cycle and earnings data from NBER and Robert Shiller.[a]
Mean earnings levels μ^s	0.0005, resp. 0.01	Earnings levels and reversions are calibrated to the mean decline of 64% in S&P 500 real earnings from peak to trough across the three business cycles since 1982.
Mean reversion speeds η^s	1.75, resp. 0.5	
Instantaneous volatility	$\sigma = 25\%$	Calibration of earnings volatility based on earnings-surprises data.[b]
Trading days per year	250	Earnings and interest paid at end of each day.
Price range	$[1, 100]$	Stock can be traded at prices ranging from 5% to 500% of mean NPV.
Tick size	0.01	Tick size is about 0.625 basis points of average stock price.
Lot size	$10^{-7} \times \mathcal{S}_t$ shares	Initially 100, corresponding to the size of a round lot at NYSE.
Interest rate	$r_a = 5\%$	Annual bond yield.
Broker fee	$b_f = 2.5\%$	Annual broker fee on margin loans.
Initial/maintenance margins	50% resp. 33%	Initial margin: Federal Reserve Board's Regulation T. Maintenance margin: 'House requirement,' typically stricter than FINRA's 25%.
Transaction tax (if levied)	10 basis points	Paid by buyer of an asset. Level as in current European proposals.
Tournaments per day	4	Entry and exit rates are 10% per year. Average attrition rate of equity fund managers is 25% over a 3-year horizon for U.S. equity funds (Busse et al. 2010).

[a] National Bureau of Economic Research 'U.S. Business Cycle Expansions and Recessions' at www.nber.org/cycles.html and www.econ.yale.edu/~shiller/data/ie_data.xls.

[b] Livnat & Mendenhall (2006) compute standardized unexpected earnings (SUE) for individual firms as $(e_t - \hat{e}_t)/p_t$, where e_t is reported quarterly earnings per share, $\hat{e}_t$ is the median analyst estimate of e_t during the 90 day period running up to t, and p_t is the share price at time t. Let σ_S denote the standard deviation of SUE, assume that σ_S is representative for firms in the S&P 500 index, and let P/E denote the P/E-ratio of the S&P 500 index. The corresponding ratio based on quarterly earnings is $4P/E$, and the relative impact on aggregate S&P 500 earnings of a one standard deviation SUE from a representative firm i is $\sigma_i := 4(P/E)\sigma_S/500$. Livnat and Mendenhall estimate $\sigma_S = 3.5\%$. With a P/E ratio of 20, one has $\sigma_i = 0.56\%$. Assuming that earnings surprises are independent, which, as forecast errors, they ought to be, earnings volatility is $\sigma = \sigma_i\sqrt{4 \times 500} \approx 0.25$ per year.

Table 2: Convergence of price process. We test for a structural break in the relationship of the risk premium of the stock, $\pi_t := 1 - p_t/\mathrm{NPV}_t$, to the expected net present value of future dividends, NPV_t, towards the end of the 15 million trading days of the model solution stage. For each one of 200 independent model runs for each scenario, we collect one observation at the close of every 10,000th trading day during the last 3 million trading days for that run. For each run, we split the resulting sample of size 300, and use the first and last 100 observations for the test. This yields a total of 200 × 200 = 40,000 observations for each scenario. Letting D_t be a dummy variable that is 0 in the first half of the sample and 1 for the second half, we estimate the model $100\,\pi_t = \alpha_1 + \beta_1 \mathrm{NPV}_t + D_t(\alpha_2 + \beta_2 \mathrm{NPV}_t) + \epsilon_t$ with AR(1) disturbances and GLS. A Chow test is used to test the null hypothesis H_0 that the coefficients α_2 and β_2 are jointly zero. P-values are shown in parentheses.

	Base case	No short	No leverage	Taxation
α_1	60.088	48.244	46.597	56.832
	(0.000)	(0.000)	(0.000)	(0.000)
β_1	−1.735	−1.427	−1.250	−1.619
	(0.000)	(0.000)	(0.000)	(0.000)
α_2	0.109	0.385	−0.177	0.699
	(0.785)	(0.301)	(0.615)	(0.060)
β_2	0.006	−0.027	0.003	−0.028
	(0.753)	(0.092)	(0.843)	(0.090)
$H_0 : \alpha_2 = \beta_2 = 0$				
$F(1, 39996)$	0.089	1.000	0.265	3.541
P-value	(0.765)	(0.317)	(0.607)	(0.060)

Table 3: Summary statistics. State variables are measured at the close of each trading day, and flow variables are daily means. Short interest (long leverage) is the number of shares held short (leveraged long) in percent of the total number of shares outstanding. Forced trades are trades generated by margin calls, and forced trade volume is the volume generated by those trades. P_5 and P_{95} denote the 5th and 95th percentiles.

	#Obs	Min.	P_5	Median	Mean	P_{95}	Max.
State (1 = Exp., 0 = Contr.)	8,000,000	0	0	1	0.776	1	1
Bayesian state probability (P)	8,000,000	0.004	0.090	0.959	0.773	0.997	1.000
Earnings per share (annualized)	8,000,000	0.040	0.286	1.381	1.459	2.954	5.436
Net present value per share	8,000,000	8.83	14.20	21.10	20.23	24.44	27.05
Closing price	8,000,000	1.00	8.77	16.39	15.85	21.50	100.00
Risk premium	8,000,000	-3.65	0.08	0.21	0.23	0.42	0.94
Bid-ask spread (bp)	8,000,000	1.00	4.75	7.50	12.84	38.52	6141.2
Quantity at bid (1,000 shares)	7,999,992	0.1	0.4	22.1	81.3	304.4	86,202
Quantity at ask (1,000 shares)	7,999,987	0.1	0.5	21.5	74.4	285.3	84,699
Order size (shares)	8,000,000	232	847	2,438	3,347	8,959	84,840
Trades	8,000,000	129	908	2,790	2,940	5,669	12,871
Turnover (%)	8,000,000	0.01	0.12	0.65	1.09	3.41	44.62
Short interest (% of outstanding)	4,000,000	0.70	3.50	8.70	9.94	20.40	82.00
Long leverage (% of outstanding)	6,000,000	0.40	1.70	5.50	6.18	12.80	30.00
Bankruptcies (% of traders)	6,000,000	0.00	0.00	0.00	0.00	0.00	12.58
Forced trades (% of trades)	6,000,000	0.00	0.00	0.00	2.29	17.50	83.15
Forced trade volume (% of vol.)	6,000,000	0.00	0.00	0.00	0.56	2.71	88.07

Table 4: Distribution of wealth under management by investors' portfolio position. Let $(\alpha, \beta) := (S/\mathcal{S}, B/\mathcal{B})$ for a portfolio with S stocks and B bonds, where $(\mathcal{S}, \mathcal{B})$ is the current number of stocks and bonds outstanding. If $\alpha + \beta > 0$, we define $\lambda = \alpha/(\alpha + \beta)$ and classify the portfolio as *Short* if $\lambda < -0.05$; *All bond* if $-0.05 \leq \lambda < 0.05$; *Overweight bond* if $0.05 \leq \lambda < 0.35$; *Market portfolio* if $0.35 \leq \lambda < 0.65$; *Overweight stock* if $0.65 \leq \lambda < 0.95$; *All stock* if $0.95 \leq \lambda < 1.05$; and *Leveraged long* if $\lambda \geq 1.05$. If $\alpha + \beta \leq 0$, the portfolio is classified as *Short* if $\alpha < 0$, and as *Leveraged long* if $\beta < 0$. Investors with portfolios such that $\alpha \leq 0$ and $\beta \leq 0$ are bankrupt and excluded from the classification. For each trading day, we compute a histogram $w()$ on the bins of this classification, where $w(P)$ is the percentage of total wealth managed by investors in portfolio position P. These histograms are aggregated by run. The entries in the table are the mean values of $w(P)$ for each scenario and portfolio position. For the base case, the p-values in parentheses refer to one-sample t-tests of zero means. For the other scenarios, they refer to paired t-tests of differences in means between that scenario and the base case. The number of observations is 200 in each scenario.

Position	Base case	No short	No leverage	Taxation
Short	4.06			4.62
	(0.000)			(0.000)
All bond	2.49	6.35	10.47	1.12
	(0.000)	(0.000)	(0.000)	(0.000)
Overweight bond	13.39	29.09	11.75	9.69
	(0.000)	(0.000)	(0.028)	(0.000)
Market portfolio	45.14	42.49	47.35	53.15
	(0.000)	(0.074)	(0.115)	(0.000)
Overweight stock	24.32	10.76	13.43	23.16
	(0.000)	(0.000)	(0.000)	(0.261)
All stock	5.46	3.83	17.00	3.90
	(0.000)	(0.001)	(0.000)	(0.000)
Leveraged long	5.10	7.48		4.34
	(0.000)	(0.000)		(0.000)

Table 5: Trading activity by investors' portfolio positions. Trading activity $\tau(P)$ is defined as the ratio of trading volume per unit of wealth under management by investors in position P, relative to the average across all investors. The percentage of total trade volume by investors in position P, $v(P)$, is calculated on the same bins as $w(P)$ in Table 4. Trading activity is given by $\tau(P) = v(P)/w(P)$. Investors with trading activity above (below) 1 have a larger (smaller) trading volume than the average investor per unit of wealth. P-values in parentheses are calculated as in Table 4. The number of observations is 200 in each scenario.

Position	Base case	No short	No leverage	Taxation
Short	5.33			6.26
	(0.000)			(0.000)
All bond	6.63	3.75	2.25	12.78
	(0.000)	(0.000)	(0.000)	(0.000)
Overweight bond	1.41	1.06	2.44	1.67
	(0.000)	(0.000)	(0.000)	(0.005)
Market portfolio	0.39	0.49	0.52	0.32
	(0.000)	(0.000)	(0.000)	(0.000)
Overweight stock	0.48	1.29	1.60	0.46
	(0.000)	(0.000)	(0.000)	(0.537)
All stock	2.42	4.99	1.55	3.92
	(0.000)	(0.000)	(0.000)	(0.000)
Leveraged long	5.24	3.96		6.72
	(0.000)	(0.000)		(0.000)

Table 6: Factor analysis of trading styles. The data consist of a random sample of two million executed trades from each scenario. Variables B_1-B_4 represent trader characteristics and behavior, including a limit order dummy (B_3) and a measure of the distance of the trader's portfolio from the market portfolio (B_4). Variables I_1-I_8 represent information usage, measured as the sensitivity of trading decisions to changes in the information available when the order was submitted. Raw data consist of vectors of indicator variables, where 1 indicates that a change in the relevant variable changed the quoted price by at least one tick or the order quantity by at least one lot. Vectors of indicator variables are divided by their sum (if positive) to obtain a measure of the extent to which the trade was based on selective information. Variables representing order book quantities are excluded to avoid multi-collinearity, and the data are standardized by run to control for run level fixed effects. The table shows the results of estimating a three-factor model with maximum likelihood and varimax rotation for each scenario. White and black circles correspond to positive and negative factor loadings, respectively, and circle areas represent absolute values. In the tax scenario, the ordering of factors 2 and 3 is swapped to match their ordering by explained variance in the other scenarios.

		Base case			No short			No leverage			Taxation		
No.	Variable / Factor	F_1	F_2	F_3	F_1	F_2	F_3	F_1	F_2	F_3	F_1	F_2	F_3
B_1	Size (log relative wealth)												
B_2	Relative trade volume												
B_3	Limit order												
B_4	Dist. from mkt portfolio												
I_1	Bid-ask spread												
I_2	Stock holdings												
I_3	Bond holdings												
I_4	Prices												
I_5	Net present value (NPV)												
I_6	Price change												
I_7	Change in NPV												
I_8	Margin account												
	SS loadings	2.20	1.50	1.49	2.84	1.45	1.38	2.07	1.76	1.24	2.44	1.13	1.41
	Proportion Var.	0.18	0.12	0.12	0.24	0.12	0.11	0.17	0.15	0.10	0.20	0.09	0.12
	Cumulative Var.	0.18	0.31	0.43	0.24	0.36	0.47	0.17	0.32	0.42	0.20	0.30	0.42

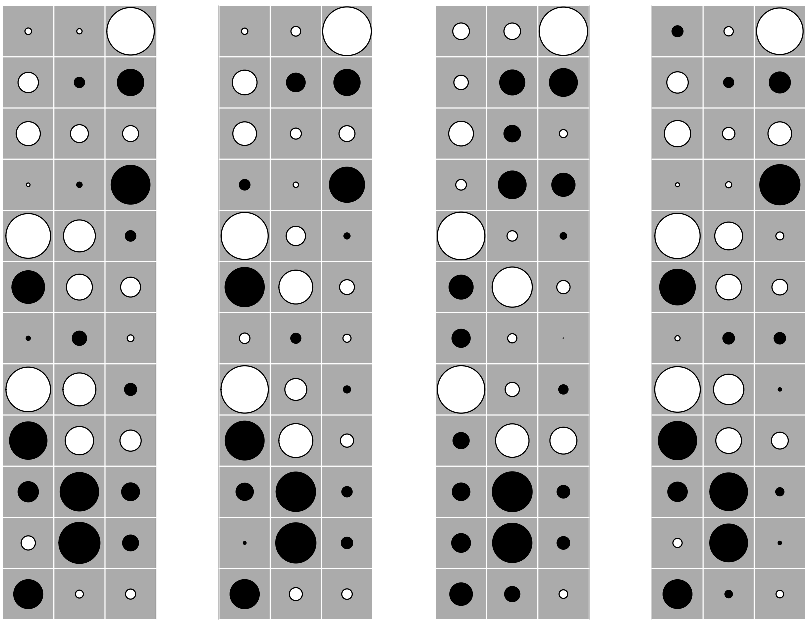

Table 7: Trading styles. Executed orders are classified by proxy variables for selected styles identified in Table 6, using the raw data of Table 6. The proxies are defined as $T_1 = (B_3 \wedge I_1) \wedge \neg I_5$; $T_2 = (I_4 \wedge I_5) \wedge \neg (I_6 \wedge I_7)$; $T_3 = (I_6 \wedge I_7) \wedge \neg (I_4 \wedge I_5)$; and $T_4 = (I_4 \wedge I_5) \vee (I_6 \wedge I_7)$. The table contains means of relative frequencies computed by run for each variable and scenario. Percentages do not add up to 100 because the classification is neither exhaustive nor mutually exclusive. P-values in parentheses are calculated as in Table 4. The number of observations is 200 in each scenario.

No.	Variable	Base case	No short	No leverage	Taxation
T_1	Liquidity suppliers	18.7%	17.1%	16.8%	19.0%
		(0.000)	(0.091)	(0.061)	(0.766)
T_2	Value traders	24.6%	21.9%	32.4%	16.7%
		(0.000)	(0.208)	(0.001)	(0.000)
T_3	News traders / arbs.	41.9%	49.6%	36.5%	47.3%
		(0.000)	(0.000)	(0.011)	(0.012)
T_4	Informed traders	83.3%	85.2%	82.0%	78.2%
		(0.000)	(0.100)	(0.296)	(0.000)

Table 8: Net liquidity supply. The data are annual means of daily observations of $100(v_L(P) - v_M(P))/(v_L(P) + v_M(P))$, where $v_L(P)$ is the limit order volume of all traders moving in or out of position P, and $v_M(P)$ is the corresponding market order volume. P-values and classification of portfolio positions as in Table 4. The number of observations is 200 in each scenario.

Position	Base case	No short	No leverage	Taxation
Short	-4.28			-14.62
	(0.000)			(0.000)
All bond	-1.51	6.00	-1.48	-5.91
	(0.001)	(0.000)	(0.957)	(0.000)
Overweight bond	4.39	4.50	-0.66	10.61
	(0.000)	(0.847)	(0.000)	(0.000)
Market portfolio	4.04	4.41	-0.82	11.85
	(0.000)	(0.500)	(0.000)	(0.000)
Overweight stock	2.63	2.03	2.91	7.96
	(0.000)	(0.146)	(0.485)	(0.000)
All stock	-3.44	-7.19	0.06	-5.37
	(0.000)	(0.000)	(0.000)	(0.000)
Leveraged long	-1.80	-9.73		-4.47
	(0.000)	(0.000)		(0.000)

Table 9: Liquidity. The data set consists of run means of daily observations of each variable. For each day, the closing bid and ask are computed as the median bid and ask across the last 50 of 20,000 intraday time steps. The *bid-ask spread* is the difference between the closing ask and bid. *Market impact* is the difference between the current bid (ask) and the average execution price of a market sell (buy) order. Market impact is calculated as (i) the average market impact across all market orders submitted during the day (endogenous order size), and (ii) the average market impact of one large buy order and one large sell order of 50,000 shares submitted at the close. The large order size corresponds to 0.2% of the average daily trade volume in the base case. In the table, spreads and market impacts are reported in *basis points (bp)* relative to the mid price. *Average order size* on a given day is calculated as trade volume divided by the number of trades. *Days between trades* is the average time, measured in days, between two consecutive trades by the same investor, calculated as the number of investors (20,000) divided by the number of trades on the given day. *Turnover per day* is trade volume divided by the number of shares outstanding (10 million shares). *Round-trip cost* is the total cost, including taxes, of buying and selling a volume equal to the endogenous order size using market orders. P-values in parentheses are calculated as in Table 4. The number of observations is 200 in each scenario.

	Base case	No short	No leverage	Taxation
Bid-ask spread (bp)	10.18	9.60	10.93	20.64
	(0.000)	(0.059)	(0.015)	(0.000)
Market impact (bp)	1.07	0.91	1.96	5.26
(endogenous)	(0.000)	(0.013)	(0.000)	(0.000)
Market impact (bp)	3.11	5.00	13.14	12.34
(50,000 shares)	(0.000)	(0.000)	(0.000)	(0.000)
Average order size	6,067	3,330	2,012	1,980
(number of shares)	(0.000)	(0.000)	(0.000)	(0.000)
Days between trades	5.23	6.21	17.73	8.95
	(0.000)	(0.000)	(0.000)	(0.000)
Turnover per day	2.46%	1.15%	0.24%	0.49%
	(0.000)	(0.000)	(0.000)	(0.000)
Round-trip cost (bp)	12.32	11.43	14.85	51.16

Table 10: Long swings in asset prices. For each scenario, *Peak-to-trough* is the mean percentage decline in the stock price from the peak in an expansion to the trough in the subsequent recession. An expansion (recession) is defined as an interval of trading days $T = \{t_1, ..., t_k\}$ such that the state variable s_t is 1 (0) on all days in T and 0 (1) on days $t_1 - 1$ and $t_k + 1$. There are 687 of these events across the 200 independent runs of the model. *High* (*Low*) is the mean across 200 runs of the maximum (minimum) closing stock price across all 10,000 trading days of that run. *Range* is the difference between *High* and *Low*. For the base case, the p-values in parentheses refer to one-sample t-tests of zero means. For the other scenarios, they refer to paired t-tests of differences in means between that scenario and the base case.

	# obs.	Base case	No short	No leverage	Taxation
Peak-to-trough	4 × 687	43.1%	39.6%	38.3%	42.4%
		(0.000)	(0.000)	(0.000)	(0.055)
High	4 × 200	21.49	22.15	21.55	21.59
		(0.000)	(0.100)	(0.872)	(0.781)
Low	4 × 200	8.16	9.37	9.39	8.48
		(0.000)	(0.000)	(0.000)	(0.004)
Range	4 × 200	13.33	12.78	12.15	13.11
		(0.000)	(0.200)	(0.002)	(0.513)

Table 11: Comovement of selected market indicators with the net present value of the stock (NPV). For each scenario, we sort all data records (200 × 10,000) by NPV, split the data set into 1,000 bins of size 0.1%, and compute the mean of each variable on the 2,000 observations of each bin. The mean NPV of each bin is identical across scenarios because the realizations of NPV are identical by run. We regress each variable on NPV by OLS for each scenario and report the coefficient on NPV. For the base case, we also report p-values in parenthesis. For the other scenarios, the p-values refer to tests of differences in the coefficients on NPV relative to the base case. The number of observations is 1,000 for each scenario.

	Base case	No short	No leverage	Taxation
Risk premium	−1.952	−1.602	−1.396	−1.889
	(0.000)	(0.000)	(0.000)	(0.000)
Short interest	−1.164			−1.059
	(0.000)			(0.000)
Long leverage	−0.007	0.231		0.079
	(0.000)	(0.000)		(0.000)

Table 12: Price fluctuations and price discovery. For each scenario and run, we calculate the R^2 obtained by regressing daily log returns on daily log innovations in the NPV of the stock. Upside and downside R^2 are calculated in the same way, except for restricting the data to days with a non-decreasing and decreasing NPV, respectively. Downside-minus-upside R^2 is the difference between the downside and the upside R^2. Annualized volatility, skewness and excess kurtosis are calculated by run from daily log-returns. P-values in parentheses are calculated as in Table 4. The number of observations is 200 in each scenario.

	Base case	No short	No leverage	Taxation
Stock price	15.37	16.45	16.10	15.47
	(0.000)	(0.000)	(0.000)	(0.388)
R^2	0.874	0.939	0.943	0.830
	(0.000)	(0.000)	(0.000)	(0.000)
R^2 down-up	0.037	0.008	0.014	0.041
	(0.000)	(0.000)	(0.000)	(0.482)
Volatility (annualized)	17.36	14.73	14.29	16.53
	(0.000)	(0.000)	(0.000)	(0.010)
Skewness	0.08	-0.31	-0.22	-0.01
	(0.323)	(0.000)	(0.000)	(0.279)
Excess kurtosis	18.34	7.27	5.55	10.45
	(0.000)	(0.003)	(0.000)	(0.021)

Table 13: Margin trading during extreme events. For each scenario and run, we identify the most extreme event, defined as the 5-day period that maximizes the range of the log closing stock price p across all 5-day periods of that run. For each extreme event, we collect information about changes in the log stock price Δp, short interest ΔSI, and long leverage ΔLL. We also compute net margin trade $\Delta(LL - SI)$. All variables are normalized by their respective standard deviations computed by run on the full samples. The table contains conditional means and medians for each variable for negative extreme events, $\Delta p < 0$, and positive extreme events, $\Delta p > 0$. For the base case, the p-values refer to one-sample Wilcoxon tests. For the other scenarios, they refer to Mann-Whitney U tests of differences between that scenario and the base case. The number of observations is 200 in each scenario.

	Base case		No short		Taxation	
	$\Delta p < 0$	$\Delta p > 0$	$\Delta p < 0$	$\Delta p > 0$	$\Delta p < 0$	$\Delta p > 0$
Change in short interest						
Mean	5.53	-10.69			5.62	-12.78
Median	4.78	-6.43			5.18	-9.26
P-value	(0.000)	(0.000)			(0.653)	(0.077)
Change in long leverage						
Mean	4.02	-2.62	4.97	-3.62	6.05	-4.56
Median	4.32	-2.36	6.02	-3.88	6.56	-4.62
P-value	(0.000)	(0.000)	(0.004)	(0.128)	(0.000)	(0.001)
Net margin trade						
Mean	-2.44	8.76	4.97	-3.62	-1.06	9.77
Median	-1.68	3.24	6.02	-3.88	-0.79	5.20
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.668)
Change in stock price						
Mean	-8.96	11.42	-8.77	8.03	-9.27	10.11
Median	-8.58	9.83	-8.30	7.84	-8.57	8.85
P-value	(0.000)	(0.000)	(0.286)	(0.000)	(0.584)	(0.054)
Number of observations	122	78	155	45	118	82