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Costs and Benefits of Financial Regulation: Short-Selling Bans and Transaction Taxes

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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 these measures are neither as beneficial as some politicians believe nor as damaging as many practitioners fear.

Keywords: Financial regulation; portfolio management; market microstructure.

JEL classification: D53; G18; C63.

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1 Introduction

Regulatory reform of capital markets is high on policy makers' agenda. Since the 2007 crisis, financial transaction taxes and bans on short selling have seen strong political support. More than 30 countries implemented short-selling bans in 2008, and the dominant member states of the European Union are determined to impose financial transaction taxes. Policy makers praise both measures for their ability to stabilize markets. Financial practitioners, in contrast, claim that these regulations reduce liquidity and therefore have a negative effect on market resilience and capital costs.

Our research starts from the premise that these differences of opinion are due to the lack of a common framework of reference in which to assess the validity of the different claims. The finance literature emphasizes the impact of regulation on liquidity, price discovery and volatility, while economists tend to be more concerned with speculative trading and excessive risk-taking. We attempt to bridge the gap by integrating trading and portfolio management in a numerical model with market microstructure and heterogeneous agents.[1] The goal is to provide a framework which represents a wide range of potentially important mechanisms, and where the equilibrium effects of these mechanisms can be measured and compared in a coherent manner. To this end, the model offers an unparalleled amount of detailed information on portfolio holdings, order flow, liquidity, cost of capital, price discovery, short-term volatility and long-term price dynamics. Since the interrelation between portfolio holdings, liquidity and trading decisions is likely to be of critical importance during periods of market distress, the model contains an exogenous business cycle process that will enable us to quantify the effect of regulation on long swings in asset prices.

The model is populated by a large number of fund managers who use quantitative strategies to manage portfolios of stocks and bonds on behalf of their clients. Assets can be traded by submitting orders to an exchange which operates a continuous double auction. Com-

[1]The potential insights from integrating trading with portfolio management were pointed out by Parlour & Seppi (2008).

petition among funds is modeled as a multiperiod tournament based on past performance. Brown, Harlow & Starks (1996) and Brown, Goetzmann & Park (2001) have demonstrated that models of this type capture many of the empirical regularities associated with the entry and exit of managed funds. Survival depends on realized performance, with new entrants exerting pressure on low-performing funds by increasing their risk of client attrition.[2]

To solve the model, we represent the quantitative trading strategies of individual funds as computer programs, and apply a genetic programming algorithm to capture the processes of competition and innovation in the market for portfolio management services. Funds participate in tournaments, with poorly performing funds being replaced by new entrants whose strategies are obtained by copying, crossing and mutating the computer programs of the winners.[3]

An important feature of this modeling approach is that risk preferences and trading strategies are endogenous. As in the adaptive market hypothesis (Lo 2004), explicit assumptions about risk preferences are neither required nor sensible because only those funds survive whose risk preferences are optimally adapted to the market. The model implements the 'as if' view of evolution and profit maximization that was introduced by Alchian (1950), where an equilibrium is obtained as the long-run outcome of the evolutionary process. We run the model for a large number of trading days and check for convergence to an equilibrium by (a) testing for structural breaks in the relationship between market prices and risk-neutral asset prices, and (b) estimating a stochastic discount factor model to test whether the market prices of the converged model are consistent with a rational expectations equilibrium.

In this paper, we apply the modeling framework to forecast the equilibrium effects of financial transaction taxes and constraints on short selling and leverage. Four regulatory scenarios are considered: (i) A benchmark scenario, calibrated to the S&P 500 index and current U.S. stock market regulations, where trade is subject to initial and maintenance

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

[3]Evolutionary algorithms were first used by Barricelli (1954).

margin requirements and no transaction tax is levied; (ii) a short-selling ban, corresponding to a permanent and global implementation of the ban of short selling 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.

Policy implications. Our results provide guidance for policy makers by quantifying the effects of regulation on portfolio holdings, order flow, liquidity, cost of capital, price discovery, short-term volatility and long-term price dynamics. We find that good market liquidity comes at the cost of high short-term volatility and enhanced long swings in asset prices. Informational efficiency of prices, however, 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-selling ban provides a compromise but with the additional benefit of a lower cost of capital. Financial transaction taxes, in contrast, entail costs but no significant benefits. These results imply that the current push for financial transaction taxes, despite its underlying fiscal goals, is a poor policy that will harm markets. In contrast, a ban on short selling promises to achieve at least some of the policy makers' aims. A detailed discussion of the results follows.

Benchmark. 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. Average daily turnover is 2.5% of outstanding shares, and the quoted bid-ask spread is approximately 10 basis points.

We observe a high degree of heterogeneity with respect to investment strategies. However, we find that funds can be classified by a small number of common styles which can be interpreted as value trading, news trading/arbitrage and market making/liquidity supply. There is a strong size effect with smaller funds tending to hold extreme positions and submit large orders relative to wealth under management.

The most active traders are leveraged funds with speculative trading strategies. Just over 9% of wealth is held by these funds, but they contribute half of the trading volume. We find that trades by leveraged funds tend to cause transient price volatility which is exploited by informed traders. Leveraged funds are liquidity takers, while funds that make long-term investments in the market portfolio are net liquidity suppliers. We find that speculators, by being net liquidity consumers, stimulate liquidity supply which leads to an increase in market liquidity in equilibrium.

On average, stocks trade at a 25% discount to their risk-neutral price, which suggests that the representative fund is mildly risk-averse. This discount is strongly counter-cyclical. Short selling contributes to high discounts during recessions. In part this is an effect of delegated portfolio management due to the principle-agent relationship identified in Shleifer & Vishny (1997). Short positions are increased when stock prices fall because short sellers outperform the market during these periods. In rising markets, the opposite is true. This leads to counter-cyclical short interest in our model. During recessions, short sellers' positions are bets on bankruptcies or financial restructuring of companies in the real economy. Either event will reduce or even clear their short positions at no cost which implies that the short-term realized performance of short sellers is better than the market average. Occasionally, this mechanism leads to bear runs which 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.

We also observe short squeezes which can occur when some short sellers are forced to buy due to margin violations. When the resulting buy pressure causes the price to rise, more margin calls can ensue which further increases demand for the stock. We find that in these situations funds with leveraged long positions act as sellers. Their supply, however, does not fully satisfy the demand from distressed buyers, thus causing overvaluation. By waiting rather than selling now, leveraged long funds keep the option of selling later to even more distressed buyers.

Transaction tax. 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.[4]

We find that a tax on financial transactions has a strong negative impact on trading activity and liquidity. This is due to an increase in transaction costs which in part is a direct effect of the tax. However, the tax also has an indirect effect of roughly the same size due to wider bid-ask spreads and greater market impact. The increase in the bid-ask spread is a partial compensation to market makers for the additional cost of doing business after imposition of the tax. Of the total tax burden, 97.5% is borne by liquidity takers.

Higher transaction costs lead to more long-term investment in the market portfolio, as suggested by the proponents of the tax. However, the wealth held by leveraged funds is only slightly reduced to just below 9% of total investment. Differences in trading activity also persist. In this sense, the tax fails to deter speculation. The model illustrates that a tax on trading has a negligible effect on portfolio holdings as it does not alter the incentive to hold short or leveraged long positions. For the same reason, we find no evidence that the tax reduces long swings in asset prices. Price discovery is less efficient, but volatility is slightly lower than in the benchmark scenario. The cost of capital is unchanged because the tax applies to purchases of equity as well as debt.

Short-selling ban. Empirical studies find that bans on short selling have an asymmetric

[4]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' 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).

effect on price efficiency, Bris, Goetzmann & Zhu (2007). Other empirical papers find that short-selling bans reduce volatility (Chang, Cheng & Yu 2007) and increase stock prices (Chang, Cheng, Pinegar & 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.

We find that a ban on short selling reduces trading activity to about half the benchmark level, but without increasing 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. The ban on short positions has a direct impact on speculators and market makers. Funds that seek risky positions are forced to move into leveraged long strategies which leads to an increase of wealth held in leveraged long portfolios by 50%. Large passive funds are less affected by the ban. The equilibrium effect is a reduction in transaction costs, a calmer market with slightly improved price efficiency, and substantially lower volatility.

Short-selling bans, by their very mechanics, curb speculative bear runs. Indeed, we find less severe decline in prices during recessions which dampens long swings in asset prices. Less downward pressure on prices during downturns and lower volatility have a positive effect on the cost of capital which is substantially reduced by a 7% increase in the average stock price.

Empirical studies of the 2008 short-selling ban draw more negative conclusions:[5] Increased trading costs through wider bid-ask spreads; reduced order book depth; and poorer price discovery. To study these short-term effects, we simulate a ban on short selling that is imposed after a prolonged period of severe decline in prices. We find that the temporary market dynamics differs from that observed in equilibrium. During the simulated 15-day ban, percentage volume-weighted spreads and 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. Differences in stock prices and trading activity between the two scenarios increase through-

[5]See, e.g., Battalio & Schultz (2011), Beber & Pagano (2013), Boehmer, Jones & Zhang (2010), Boulton & Braga-Alves (2010), Kolasinksi, Reed & Thornock (2010), and Marsh & Payne (2012).

out 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-selling ban, while higher transaction costs are a temporary phenomenon associated with an unexpected change in the regulatory regime.

Leverage ban. Although a ban of all short and leveraged long positions might be impossible to enforce in practice, this scenario provides additional insight into the role of leverage for trading and market stability. As the funds' ability to trade on differences in opinion is curtailed, trade volume is reduced by 90% relative to the benchmark level. The order book is extremely shallow, but effective trading costs are only marginally higher than in the benchmark scenario due to the drop in trade volume. Supplying liquidity becomes less profitable and trading focuses more on value than on news. This shift in funds' focus coincides with the lowest volatility of daily returns across all scenarios. By curbing both bear runs and speculative bubbles, the leverage ban reduces long swings further compared to a short-selling ban.

2 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.

2.1 Market and investors

Real economy. The real economy is represented by one aggregate firm whose equity and debt are publicly traded. The aggregate firm generates daily earnings per share which are determined by a geometric Ornstein-Uhlenbeck process with time-varying mean. The specification of the firm's 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 $1/\nu^{s_t}$ where $\nu^1 > \nu^0$. Earnings exhibit short-term volatility σ and a medium-term trend $\eta^{s_t}(\mu^{s_t} - e_t)$.[6]

The earnings process is observable, but the state of the economy is not. An estimate of the probability distribution over the possible states of the economy is provided using Bayes' rule. Denote by P_t the Bayesian estimate of the probability that the current state s_t is 1. The time in years between two earnings observations is given by $\Delta = 1/(250 \cdot 100)$. Given a prior P_t and a new earnings observation $e_{t+\Delta}$, the realized earnings growth is $R^e_{t+\Delta} = (e_{t+\Delta} - e_t)/e_t$. Its distribution is normal, see (1). The posterior $P_{t+\Delta}$ is given by

$$P_{t+\Delta} = \frac{\exp(-\Delta/\nu^0)(1 - P_t)\beta^0_{t+\Delta} + [1 - \exp(-\Delta/\nu^1)]P_t\beta^1_{t+\Delta}}{(1 - P_t)\beta^0_{t+\Delta} + P_t\beta^1_{t+\Delta}}$$

where, for $s = 0, 1$,

$$\beta^s_{t+\Delta} = \frac{1}{\sqrt{2\pi\Delta}\sigma} \exp\left(-\frac{[R^e_{t+\Delta} - \eta^s(\mu^s - e_t)\Delta]^2}{2\sigma^2\Delta}\right).$$

The risk-neutral value of the earnings process with current state e_t and Bayesian estimate P_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 risk-neutral value of the future earnings for an economy in state s

[6] Information about the earnings process is updated 100 times per day. Actual earnings payments are determined by the value of e_t at the end of each trading day.

with current earnings e_t. $V^s(e_t)$ is calculated as the expectation of $\sum_{k=0}^{\infty} \exp(-rk\Delta)e_{t+k\Delta}$ conditional on $s_t = s$, cf. Veronesi (1999).

Financial securities. The aggregate firm issues stock and bonds. 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.

We do not model the firm's financing decision but assume that it keeps debt per share constant at $d := d_0$. At the end of every trading day the firm issues new shares and bonds in proportions $1 : d$. The proceeds are used to increase the scale of its operations, which is proportional to the number of shares outstanding. 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 yields a total proceeds of $\mathcal{S}_t e_t$, equal to the total income of investors.

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.[7] Market orders are executed at the best price offered by the current standing

[7]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. We do not model individual lender-borrower contracts but impose that constraint that the supply of stock available for borrowing cannot exceed 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.[8]

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. A portfolio (B_t, S_t) held at the end of a trading day receives the amount

$$r\,B_t + (e_t - rd)\,S_t - b_f L_t, \tag{3}$$

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

[8] 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.

is

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

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.[9]

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 shares meets the margin requirement M_t provided

$$\mathrm{M}_t |p_t S_t| \leq B_t + p_t S_t, \tag{4}$$

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 therefore 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-selling 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.

[9] 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.

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.

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 fund follows a quantitative trading strategy which determines the current limit order, i.e., a price-quantity pair, as a function of the information available at the time of order submission. A trader's information comprises knowledge about the order book (bid, ask, and the quantities available at these prices), the risk-neutral value of the earnings process, changes in the stock mid price and risk-neutral value 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 issuing 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. Real numbers are 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.

Closing the model. The model generates a residual flow of claims which consists of tax payments, broker fees, portfolio holdings of bankrupt funds, and portfolio holdings of funds that enter and exit the market via tournaments. Terminated funds relinquish their portfolio holdings, and new funds receive 20% of the average portfolio. The net flows of shares and bonds are accumulated on a daily basis, and the current balances are redistributed among all existing funds at a rate of 1% per day in proportion to their managed wealth.

2.2 Solution algorithm

The model is solved using a genetic programming (GP) algorithm with tournament selection (Koza 1992). The GP algorithm approximates an equilibrium by searching for new strategies that outperform existing ones until the market is weak-form efficient and the distribution of strategies is stable. The outcome of this search is a set of heterogeneous strategies which are adapted to the institutional setting and geared towards survival.[10]

Tournament selection is based on the model for the entry and exit of managed funds proposed by Brown et al. (1996) and Brown et al. (2001). We use wealth under management as a proxy for past performance. The ranking position of funds that recently entered the market is dominated by short-term realized returns because all funds enter the market with the same initial endowment. Consequently, small differences in recent realized returns have a strong effect on the ranking position of new funds. The situation is different for large,

[10]The implementation mimics the principles of Darwinian selection and reproduction by breeding populations of traders that pursue more profitable strategies than their predecessors. More successful strategies are more likely to be passed on to the new generation akin to better adapted living organisms expanding at the expense of those with lower chances of survival. Genetic algorithms were introduced by Holland (1975), and have proved successful in many engineering fields. For applications in financial economics, see, e.g., Arifovic (1996), Lensberg & Schenk-Hoppé (2007), and Noe, Rebello & Wang (2003, 2006).

established funds whose longevity is due to superior past performance. These funds typically have only few competitors with a similar amount of wealth under management, and their ranking position is therefore less dependent on short-term performance.

The GP algorithm operates on the computer programs which define the trading strategies of funds. The computer programs are implemented in machine code following Nordin (1997). Each program consists of a list of at most 128 machine instructions which operate on variables and constants stored in memory, using the CPU floating point registers to store and manipulate temporary variables. An instruction specifies an operator and one or two operands. Operators consist of +, -, /, $\times$, *maximum, minimum, 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 order (a price and a quantity) is determined by the values of the first two temporary variables after the program has executed.

The algorithm starts by randomly generating a computer program for each fund. From this initial state, trading proceeds as explained in Section 2.1. Over many trading days, the algorithm replaces low performing programs with genetic recombinations of high performing ones as follows: At the end of every trading day, there are tournaments where underperforming fund managers are replaced by new entrants who either follow investment strategies that performed well in the past or random modifications of those strategies. The programs of market entrants are derived using the standard genetic operators crossover and mutation. Our implementation of the algorithm is as follows:

1. *Tournament:* Randomly select eight programs from the trader population and rank them according to wealth under management.

2. *Reproduction:* Replace the two programs with the lowest rank by copies of the strategies of the two with the highest rank.

3. *Crossover:* With probability χ_1, recombine the genetic material of the two copied programs by swapping one randomly selected sublists of instructions between the two programs.

4. *Mutation:* Each of the two programs copied undergoes a mutation with probability χ_2: a single operation or operand in a program is randomly selected, and replaced with a randomly generated instruction.

Table 1 illustrates some aspects of the machine code GP algorithm by means of an example in which the maximum program length is limited to 6 instructions and there are only two input and one output variable.

The algorithm is run with a population of size 20,000 and four tournaments at the end of each day. The mutation and crossover probabilities are set to $\chi_1 = 0.5$ and $\chi_2 = 0.9$. A model run consists of two stages: Solution and data collection. The number of trading days for the solution stage is identical across scenarios and large enough to ensure convergence. Data are then collected during an additional 10,000 trading days.

2.3 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 2 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.

The data set comprises time series of all investors' orders and portfolio holdings, the order book, and information about prices, earnings and risk-neutral stock prices. It contains 200 independent time series over 10,000 trading days for each scenario. 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.

The risk-neutral stock price (RNP) is defined as $v(P_t, e_t) = V(P_t, e_t) - d$. Here $V(P_t, e_t)$ is the risk-neutral value of the earnings process defined in (2) and d is the risk-neutral value of bonds per share which coincides with the number of bonds per share. For computational purposes $v(P_t, e_t)$ is approximated by two polynomials in $\log(e_t)$: $v^{\alpha}(e_t) = \alpha_0 + \alpha_1 \log(e_t) + ... + \alpha_4 \log^4(e_t)$, one for each state $s \in \{0, 1\}$ of the economy. The representation

$$(1 - P_t)\, v^{\alpha(0)}(e_t) + P_t\, v^{\alpha(1)}(e_t),$$

with

$$\begin{aligned}\alpha(0) &= (21.0631, -2.1233, -0.8165, -0.05959, -0.001421)\\ \alpha(1) &= (46.3463, 5.7138, 0.1622, -0.004786, -0.0002859)\end{aligned}$$

has an $R^2 > 0.999$ on a domain that includes all earnings realizations in our simulations.

We will use the risk-neutral stock price as a benchmark in the statistical analysis. To compare the market price of the stock with its RNP, we define the stock price discount $\pi_t := 1 - p_t/\mathrm{RNP}_t$. It is positive (negative) if the stock trades below (above) its RNP.

Table 3 shows that the RNP varies between 8.8 and 27, while the range of market prices is much wider and includes the predefined bounds which are set at 1 and 100. In the simulations these bounds are 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.

Convergence of the model is checked by testing for a structural break in the relationship between the discount and the RNP of the stock. We use data collected from the last 20% trading days of the model solution stage. Table 4 shows no evidence of any structural break in the time series for the first three scenarios. For the tax scenario, the evidence against the null hypothesis is stronger, but still not significant at the 5% level.

To characterize the aggregate price dynamics of the converged models, we estimate stochastic discount factors (SDFs) and examine their pricing errors. Let $R^S_{t+\Delta}$ and $R^B_{t+\Delta}$ denote the gross return on stocks and bonds during the time period from t to $t+\Delta$, and let $m_{t+\Delta}$ denote the stochastic discount factor at time t. We form the moment conditions

$$E[m_{t+\Delta}(R^S_{t+\Delta} - R^B_{t+\Delta})\mathbf{z}_t] = \mathbf{0}, \tag{5}$$

where $\mathbf{z}$ is a vector of instruments whose values $\mathbf{z}_t$ are predetermined at time t. We choose $\mathbf{z}_t = (1, R_t, P_t - P_{t-\Delta}, e_t/e_{t-\Delta})$, which contains a constant term lagged stock returns, lagged changes in the Bayesian state probability, and lagged earnings growth. The idea is that knowledge of these variables should not offer arbitrage opportunities in terms of correlations between instruments and pricing errors that would violate the moment conditions. It should be noted that the agents in our model do not know $\mathbf{z}_t$, for lag lengths greater than one day. We hypothesize that the agents will exhaust any arbitrage opportunities associated with $\mathbf{z}_t$ despite the fact that they trade on limited information.

We assume that $m_{t+\Delta}$ is proportional to $(w_t/w_{t+\Delta})^\gamma$, where w_t denotes the value of the market portfolio at time t. The parameter γ in the SDF can be thought of as the constant relative risk aversion of a representative agent with direct or indirect preferences over wealth. In view of the results on growth optimal wealth strategies and risk preferences (Kelly 1956), we hypothesize that the representative agent maximizes log utility, corresponding to $\gamma = 1$.

Table 5 reports the results of estimating the empirical counterpart to (5) with GMM on quarterly data for each scenario. The data sets consist of 160 quarters for each of the 200 model runs. The estimated risk aversion coefficient is not significantly different from 1 in any of the four scenarios, consistent with our hypothesis of log utility maximization.

The first three scenarios pass the model specification test (J-test) at the 5% significance level, but the tax scenario does not. This suggests that there are statistical arbitrage opportunities in the converged models of the tax scenario. To gauge the size of these arbitrage opportunities, we regressed the pricing errors from the GMM model on the instruments $\mathbf{z}_t$. The correlation between the actual and predicted pricing errors is 0.038, and the volatility of the actual pricing error is 0.084. This yields a predictable pricing error of $0.038 \times 0.084 = 0.0032$ (32 basis points), which is less than the average cost of a round trip in the tax scenario (51 basis points, cf. Table 11).

Figure 1 provides additional information on the short-run price dynamics of the model. Autocorrelations are small and generally 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. With a daily price volatility of about 1%, the predictable abnormal return (about 2 bp) is much too small to compensate for a 51 bp roundtrip cost. The evidence against the pricing model of the tax scenario is therefore weaker than indicated by the J-test in Table 5.

We conclude that, with a possible exception for the tax scenario, asset prices can be rationalized in terms of a representative agent with log utility of wealth. The information set of the representative agent includes knowledge of lagged returns, change in state probability, and earnings growth, in addition to the information on current variables that is explicitly given to the traders.

3 Results

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

3.1 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-selling ban, for instance, disrupted the business models of many financial firms who in turn 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.[11]

Regulation can be beneficial if it prevents investors from taking on too much risk. For instance, Robert Shiller made a case for fighting speculative bubbles through active management of margin requirements after the burst of the dot-com bubble in 2000.[12] 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.

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,

[11] http://www.sec.gov/comments/4-627/4627-139.pdf
[12] 'Margin Calls: Should the Fed Step In?,' Wall Street Journal, April 10, 2000.

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 matching that of the market ensure low volatility of the fund manager's relative performance, which reduces the risk of client attrition. Table 6 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 7 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 magnitude of short interest and trade volume generated by short sellers is comparable to empirical findings, e.g., Diether, Lee & Werner (2009) and Boehmer, Jones & Zhang (2008). Boehmer et al. (2008) find that in 2007 the short interest on NYSE was approximately 4% of outstanding shares, and that short sellers were involved in about 40% of the trade volume.

A 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 scenario 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 ban on short selling is extended to a full leverage ban.

Table 6 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-selling 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 trading 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 8. 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 strategy 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.[13] 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.

[13]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.

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. As only the first three eigenvalues are consistently greater than 1 in each scenario, the analysis suggests using three factors throughout.

Table 8 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.[14] The factor assigns positive scores to traders who are sensitive to information on market prices and RNPs, i.e., value traders. Negative scores are assigned to traders who are sensitive to daily changes in those variables, i.e., 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 RNP, but who are insensitive to price information. These traders appear to be involved in carry trades or other cyclical strategies. 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 9. 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 8.

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;

[14]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 the RNP or to changes in both variables.

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 contradicts his conjecture that the tax discourages short-term speculative trading by redirecting investors' focus towards the long term. In the tax scenario more funds hold the market portfolio. Since this strategy does not require information, there is less information acquisition in the aggregate. The shift from value investing to short-term speculation in the tax scenario coincides with the shift in relative trading activity: Leveraged funds contribute a larger proportion to the trade volume in the tax scenario than in the benchmark case, Table 7.

The results in Table 9 suggest that a full leverage ban would advance the goal of reducing the focus on the short-term, but that a ban on short selling would have the opposite effect.

3.2 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 are generally found to 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. 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. 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.[15] 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

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

actually improve.

Theoretical studies find that transaction taxes have negative effects on trade frequency and volume (Constantinides 1986, Kupiec 1996, Scheinkman & Xiong 2003). By abstracting from the market microstructure, these papers do not capture the full equilibrium effect on trading costs which can also increase as a result of wider spreads or a shallower book. In quote-driven markets, for instance, Subrahmanyam (1998) and Dupont & Lee (2007) show that the impact of a tax on trading costs depends on the competition between market-makers and the degree of information asymmetry. We therefore expect to find the tax to reduce liquidity because some investors in order-driven markets tend to specialize in liquidity provision (Sect. 3.1).

The impact of short-selling bans on liquidity in order-driven markets has only been studied from an empirical perspective. Beber & Pagano (2013) and Boehmer et al. (2010), for instance, find that the 2008 short-selling ban negatively affected liquidity. In other empirical studies of short-selling bans, e.g., Bris et al. (2007), liquidity is used as an explanatory rather than dependent variable.

We analyze the net liquidity supply of different groups of investors, and provide results on order book properties and transaction costs. Table 10 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.[16] 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 10 reveals that under a short-selling ban the largest suppliers of liquidity are active traders who

[16]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.

are constrained to holding all-bond portfolios. This effect disappears when the ban on short selling is extended to a full leverage ban because it hurts the customer base of market makers by eliminating all leveraged speculation.

Table 11 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 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 ban on short selling 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 11. A ban on short selling 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 11. 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 ban short selling 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-selling ban on trade volume and trading activity are consistent with the empirical evidence. Studies of the 2008 short-selling ban find significant negative effects on liquidity, price discovery and volatility, see, e.g., Battalio & Schultz (2011), Beber & Pagano (2013), Boehmer et al. (2010), Boulton & Braga-Alves (2010), Kolasinksi et al. (2010), and Marsh & Payne (2012). However, the dramatic increase in the transaction costs of banned stocks reported by Boehmer et al. (2010) is not observed as an equilibrium effect in the model. This suggests that some of the empirical results on short-selling bans may be due to short-run effects which are not equilibrium phenomena.

The 2008 U.S. short-selling 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 ban on short selling, 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-selling 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 RNP 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 ban on short selling 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, Namvar & Phillips (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-selling ban, while higher transaction costs are a temporary phenomenon associated with an unexpected change in the regulatory regime.

3.3 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-selling 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.

The destabilizing effects of leverage are well documented in the theoretical literature. 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.

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 12 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 ban on short selling 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 on the mean peak-to-trough decline.

Peak-to-trough movements are largely determined by the difference in average price levels observed during booms and recessions. In Table 12 the variables 'High' and 'Low' 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-selling ban. The range is narrower under a full leverage ban, but is not significantly different in the other three scenarios. Therefore, leverage restrictions reduce long swings by supporting stock prices during recessions.

The effect can be explained by analyzing differences in the cyclicality of the stock price discount across scenarios. The discount is the percentage amount by which the market price of the stock is lower than its risk-neutral price. Table 13 shows that the discount on the stock moves counter-cyclically in all scenarios, but less so in those two where short selling is banned. The more moderate reaction of the discount in these two scenarios is due to leverage restrictions reducing downward price pressure from counter-cyclical short selling. Stock prices are supported during recessions by the very mechanics of short-selling bans which curb speculative bear runs. Indeed, we observe that counter-cyclical short interest is most pronounced in the base and tax scenarios, with short positions increasing during downturns and decreasing during upturns, Table 13. This is consistent with Lamont & Stein's (2004) observation that short interest moved counter-cyclically during the dot-com bubble.

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 13.

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.

3.4 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.

It is a non-trivial empirical task to measure the effects of regulation on price discovery because 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 ban on short selling 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. In the model, these effects can be measured and related to movements in the fundamentals.

We find that stock prices are highest under the short-selling ban and lowest in the base and tax scenarios, Table 14. 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-selling ban is in line with the empirical findings of Chang et al. (2007) and the increase in stock price with those in Chang, Cheng, Pinegar & 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. In our model a short-selling ban increases the equilibrium price level by 7%, but a full leverage ban increases it by only 5%, despite lower volatility in this scenario. We attribute the difference to Miller's (1977) result on overvaluation in markets with diverging opinions and short-selling constraints.[17]

[17] Scheinkman & Xiong (2003) show that this effect persists in a dynamic model with both rational and overconfident investors.

Empirical studies find that transaction taxes lower asset prices (Schwert & Seguin 1993, Umlauf 1993, Bond, Hawkins & Klemm 2004, Matheson 2011). Most theoretical models predict that asset prices are reduced by the net present value of the effective tax, e.g., Kupiec (1996). However, Vayanos (1998) observes that transaction taxes can have two opposing effects on prices in overlapping generations models with several rounds of trade. While the tax makes purchasing the asset more costly, thus lowering demand, the tax can make sellers more reluctant to sell, thus lowering supply. The impact of the tax on the price level is therefore ambiguous. In delegated fund management, in contrast, positions are marked-to-market and there is no point in time where all assets have to be sold for consumption. Constantinides (1986) shows that the absence of forced liquidation at a terminal time implies that the tax has only a second-order effect on the price level. In our model every transaction incurs a tax because the sale of one asset requires a purchase of equal value of the other. Therefore no asset has a tax advantage, and there is no effect on the relative prices of 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 RNP. 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) RNP. R^2 and the difference between downside and upside R^2 are reported in Table 14.

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-selling ban is at odds with the empirical findings of Bris et al. (2007), but consistent with Chang, Cheng, Pinegar & 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 scenario where short selling is banned. This is consistent with Diamond & Verrecchia's (1987) prediction that restrictions on short selling 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. These effects are explained below by analyzing the impact of extreme events.

We find that price discovery is adversely affected by bear runs (Section 3.3) and short squeezes.[18] Table 15 provides details on the behavior of margin traders during extreme 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

[18]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' 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."

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 ban on short selling. When short selling is allowed, crashes and bubbles are associated with destabilizing bear runs and short squeezes, respectively. Traders who go short 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-selling 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.

These findings highlight that short selling can exacerbate bubbles, i.e., a rise in the price without the arrival of new information, because selling by leveraged long investors fails to fully offset the buy pressure from distressed short sellers. Investors who are long in the stock and do not sell now realize the intrinsic value of the option of selling later to a more distressed buyer. A ban on short selling alters this dynamic with net (long) margin trade contributing to market stability. However, Hong & Stein (2003) find that market crashes can occur when investors with private information face short-selling constraints but arbitrageurs do not. In our model, the ban is uniform which excludes such a scenario.

In the scenarios where short selling is allowed, we find that the destabilizing effect of margin trade distorts the association of returns with innovations to RNP. The effect is stronger for positive innovations to RNP due to the asymmetry between the impact of short and leveraged long positions. The former leads to higher kurtosis and lower price efficiency in terms of R^2, and the latter to less negative skewness[19] and higher downside-minus-upside R^2 (Table 14).

To a large extent, the superior price discovery of bad news in the base case is an artifact caused by a few extreme events. We quantify this effect by computing downside R^2 and upside R^2 after removing the 10 most extreme events from each run. In the base scenario upside R^2 increases three times more than downside R^2 when the 10 most extreme events are removed from each run. The same effect is observed in the short-selling ban scenario but it is one order of magnitude smaller. As a result, the difference in downside-minus-upside R^2 between the base and the short-sale ban case is reduced from 0.029 (Table 14) to 0.016. The estimate of the negative effect of the short-sale ban on price discovery in response to bad news is therefore biased upwards by more than 80%. More generally, this analysis shows that regulatory reforms can have spurious effects on standard measures of price discovery,[20] and that these effects can sometimes be identified by examining differences in price dynamics during extreme events.

4 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.

[19] Absent any asymmetric effects of trading, daily stock returns will display negative skewness because the skewness of daily innovations to RNP is negative at -0.18. Negative skewness in RNP is due to negative skewness in the Bayesian state probability, which has a median close to 1 and a fat left tail (Table 2).

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

We find that a short-selling 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 book depth. A leverage ban enhances the positive effects of the short-selling 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-selling 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 several new hypotheses for empirical investigation: (1) Introduction of a short-selling ban has a permanent effect on stock prices and trading activity, but only a temporary effect on transaction costs; (2) Evidence of inferior price discovery related to negative information about stocks subject to a short-selling ban can be accounted for by asymmetric price dynamics during extreme events; and (3) Transaction taxes shift the focus of investors from value investment to news trading.

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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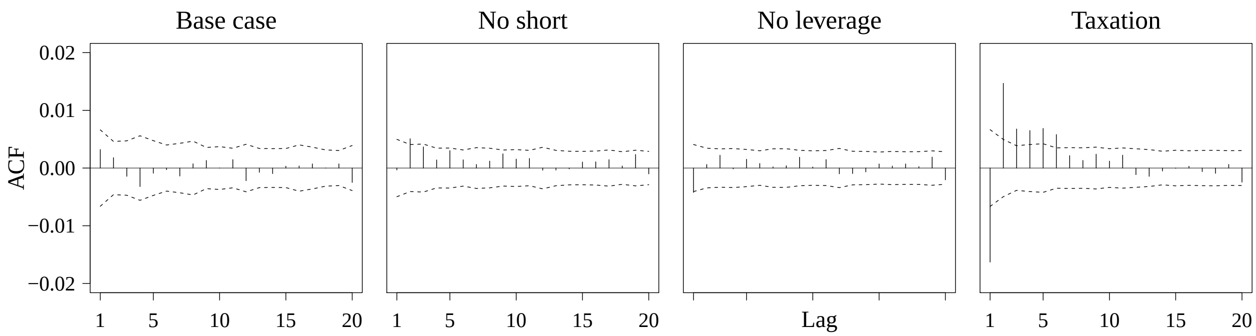


Figure 1: Autocorrelations in daily log returns. For each scenario, data are collected from 200 model runs over 10,000 trading days. The mean autocorrelation functions are computed across those 200 runs. The dashed lines connect confidence intervals of ± 2 standard errors computed at each lag.

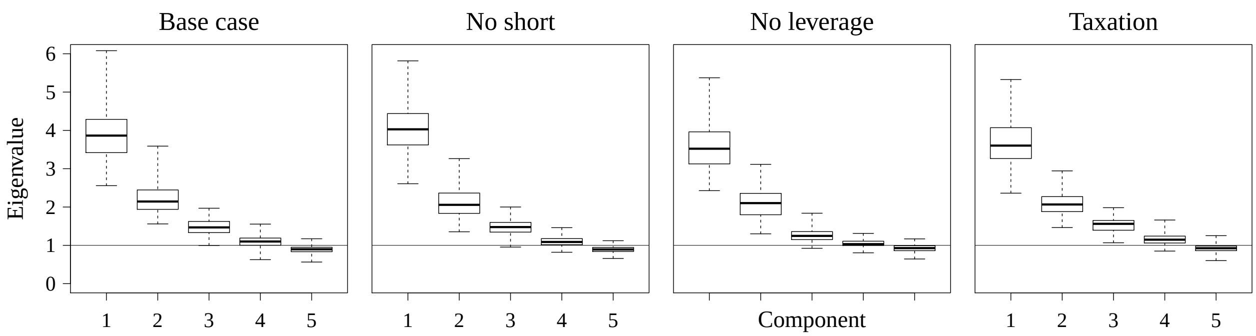


Figure 2: Eigenvalues for factor model selection. For each scenario and run, we compute the 12-dimensional correlation matrix and its eigenvalues from a random sample of 10,000 individual orders. For each scenario, the box plots show the range; the first and third quartiles; and the median of the 5 largest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

Table 1: Simplified example of the program structure and the crossover operation. R_0 and R_1 refer to floating point registers 0 and 1 of the CPU. The GP algorithm clears these registers by loading them with the value zero before passing a program to the CPU for execution. Input variables consist of two prices, the bid b and the ask a. The output is the price of a limit order. The value of the output variable is the content of register R_0 after all program instructions have been processed by the CPU. The left part of the table depicts two programs, A and B, with 5 and 6 instructions, respectively. The right part shows the outcome of a crossover at instruction slots 3-6, which produces two new programs, C and D. For instance, for Program A the output is a constant price. If, for instance, bid and ask prices were higher, then this order would either be an aggressive buy order (quantity positive) or a passive sell order (quantity negative). For Program D, the output is the mid point of the bid-ask spread. If the corresponding quantity is non-zero, this would be a price-improving order.

Instr.	Before crossover		After crossover	
slot	Program A	Program B	Program C	Program D
1	$\mathbf{R_1 = a}$	$R_0 = b$	$\mathbf{R_1 = a}$	$R_0 = b$
2	$\mathbf{R_0 = R_0 + 2}$	$R_1 = a$	$\mathbf{R_0 = R_0 + 2}$	$R_1 = a$
3	$\mathbf{R_1 = R_0 + R_1}$	$R_0 = R_0 * R_0$	$R_0 = R_0 * R_0$	$\mathbf{R_1 = R_0 + R_1}$
4	$\mathbf{R_0 = R_0/2}$	$R_0 = R_0 * R_1$	$R_0 = R_0 * R_1$	$\mathbf{R_0 = R_0/2}$
5	**Return** $\mathbf{R_0}$	$R_0 = \max(R_0, R_1)$	$R_0 = \max(R_0, R_1)$	**Return** $\mathbf{R_0}$
6		*Return* R_0	*Return* R_0	
	1	$\max(ab^2, b)$	$\max(4a, a)$	$(b + a)/2$

Table 2: 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	175, resp. 50	
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 RNP.
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 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
Risk-neutral stock price	8,000,000	8.83	14.20	21.10	20.23	24.44	27.05
Stock price	8,000,000	1.00	8.77	16.39	15.85	21.50	100.00
Stock price discount	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: Convergence of price process. We test for a structural break in the relationship between the risk-neutral stock price, RNP_t, and discount, $\pi_t := 1 - p_t/\mathrm{RNP}_t$, towards the end of the model solution stage. For each one of 200 independent model runs for each scenario, we collect 300 equally spaced trading days from the last 20% of the model solution stage. We split each sample in three 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 $100\,\pi_t = \alpha_1 + \beta_1 \mathrm{RNP}_t + D_t(\alpha_2 + \beta_2 \mathrm{RNP}_t) + \epsilon_t$ 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 5: Stochastic discount factors. Using quarterly data, we form the empirical moment conditions $(1/T)\sum_{t=1}^{T}(w_t/w_{t+1})^{\gamma}(R^S_{t+1} - R^B_{t+1})\mathbf{z}_t = \mathbf{0}$, where γ is a risk aversion parameter to be estimated, w_t/w_{t+1} denotes quarterly growth in the value of the market portfolio, and $\mathbf{z}_t = (1, R_t, P_t - P_{t-1}, e_t/e_{t-1})$. Apart from the constant term, the elements of $\mathbf{z}_t$ represent lagged stock returns, lagged changes in the Bayesian state probability, and lagged earnings growth. The number of observations per scenario is $T = 32,000$. We estimate the parameter γ with two-step GMM and use a J-test with 3 degrees of freedom to test for model misspecification.

	Base case	No short	No leverage	Taxation
Coefficient (γ)	1.180	0.971	1.121	1.161
P-value ($H_0 : \gamma = 1$)	(0.111)	(0.816)	(0.371)	(0.157)
J-test statistic	7.634	2.326	6.869	20.351
P-value ($H_0 : J = 0$)	(0.054)	(0.508)	(0.076)	(0.000)

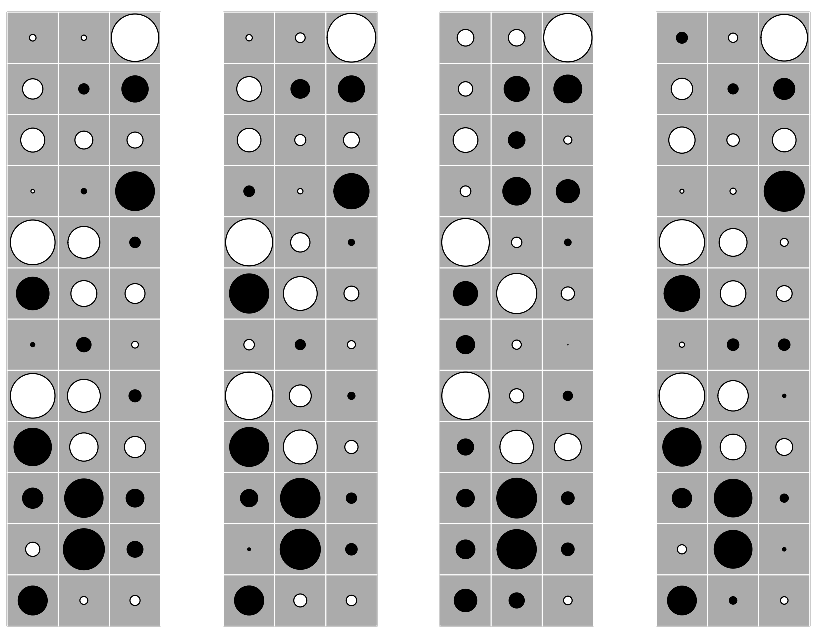
Table 6: Distribution of wealth under management by investors' portfolio position. Let $(\alpha, \beta) := (S/\mathcal{S}, B/\mathcal{B})$ for a portfolio with S stocks and B bonds, where $(\mathcal{S}, \mathcal{B})$ is the current number of stocks and bonds outstanding. If $\alpha + \beta > 0$, we define $\lambda = \alpha/(\alpha + \beta)$ 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 7: 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 6. 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 6. 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 8: 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.



No.	Variable / Factor	Base case F_1	Base case F_2	Base case F_3	No short F_1	No short F_2	No short F_3	No leverage F_1	No leverage F_2	No leverage F_3	Taxation F_1	Taxation F_2	Taxation 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	RNP												
I_6	Price change												
I_7	Change in RNP												
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 9: Trading styles. Executed orders are classified by proxy variables for selected styles identified in Table 8, using the raw data of Table 8. 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 6. 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 10: 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 6. 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 11: 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 6. 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 12: 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 13: Comovement of selected market indicators with the risk-neutral stock price (RNP). Market indicators are *discount* (percentage amount by which the market price of the stock is lower than its risk-neutral price), *short interest* (percentage amount of the value of all short positions in the stocks), and *long leverage* (percentage amount of bonds borrowed). For each scenario, we sort all data records ($200 \times 10{,}000$) by RNP, 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 RNP of each bin is identical across scenarios because the realizations of RNP are identical by run. We regress each variable on RNP by OLS for each scenario and report the coefficient on RNP. 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 RNP relative to the base case. The number of observations is 1,000 for each scenario.

	Base case	No short	No leverage	Taxation
Discount	−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 14: 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 RNP 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 RNP, 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 6. 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 15: 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

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