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PREMIO TESI D'ECCELLENZA

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2022-2023

LUISS

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Working Paper n. 4/2022-2023
Publication date: Dicember 2024
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ISBN 979-12-5596-198-7

Luiss Academy is an imprint of
Luiss University Press – Pola Srl
Viale Pola 12, 00198 Roma
Tel. 06 85225485
E-mail lup@luiss.it
www.luissuniversitypress.it

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By Elisa Monteleone

INTRODUCTION

In a constantly changing economic environment, the need to meet specific financial goals led to a growing interest in rebalancing-based investment strategies. Habitually employed by many institutional investors subject to pre-established investment mandates[1], rebalancing can be described as the “process of buying and selling assets in a portfolio to adjust their weightings back to the target allocation of the portfolio” (Kitces, 2015). Whether a deviation from a pre-agreed target rule occurs due to oscillating asset valuations, investors and funds’ managers can easily restore the original asset allocation by engaging in active portfolio management. A completely different policy drives buy-and-hold strategies: with the same securities held over the entire investment horizon, passive portfolios remain unaltered despite eventual variations in the value, return or risk profile of the assets.

The superiority of rebalancing strategies against other, more traditional, alternatives, has been widely acknowledged by the literature. A comparison of rebalanced and non-rebalanced portfolios made by Tsai (as cited by Meyer-Bullerdiek, 2018) shows that the former enjoys substantially higher risk-adjusted returns in terms of Sharpe ratios. Norges Bank (2012) documents that, over a sample spanning from 1970 to 2011, rebalanced portfolios experienced both higher returns and lower risk than passive portfolios mimicking broad market indexes. Meyer-Bullerdiek (2018) examines how rebalancing affects portfolio diversification and risk-adjusted returns, concluding that rebalanced portfolios are better diversified and enjoy, on average, higher risk-return ratios vis-à-vis their buy-and-hold counterparties. According to Kitces (2015), a rebalancing strategy offers two main benefits: first, it allows to keep the portfolio’s risk aligned with its target (*risk management*); second, it provides the possibility to exploit buy-low-sell-high opportunities to enhance returns (*return enhancement*).

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[1] Pension funds, balanced funds and sovereign wealth funds are the best examples of rebalancing institutions (Lu & Wu, 2021). Mutual funds are not straightforwardly accounted as rebalancers; still, some of them fall within this category as well.

The success and the academic attention such portfolio rebalancing device gained directly call for the identification of the dynamics behind it; to that extent, an analysis of the sources of asset prices' fluctuations should be performed as the first step. Xie, Xia and Gao (2021) link price variations to investors' limited rationality and their "dual behavior". As heterogenous agents, indeed, investors are not always able to act rationally; often, their actions are driven by market sentiment. Under such view, financial markets' volatility should be attributed to both "fundamental" (or "rational") factors – such as economic fundamentals or monetary policy – and to "sentiment" factors – subjective beliefs and overconfidence among the others. Based on such reasoning, monetary policy must be deemed as one of the concurrent and most relevant causes of asset prices volatility. Indeed, while monetary actions do not have asset prices as their main direct target, they inevitably affect them *indirectly*, through the so-called "asset pricing" or "portfolio rebalancing" channel.

Many authors provide evidence in favor of the existence of such portfolio rebalancing channel, active in the transmission of both conventional and unconventional monetary policies. Lu and Wu (2021) find out that higher rebalancer ownership has a statistically significant negative impact on US stock returns in response to restrictive monetary policy shocks. Jarociński and Karadi (2018) distinguish two kinds of shocks originating from monetary policy announcements on the grounds of their correlation with the stock market. Specifically, they identify "monetary policy shocks", which negatively comove with stock returns, as well as "central bank information shock", exhibiting instead a positive correlation with equity performance. Jovanceau (2016) investigates the impact of quantitative easing on a set of corporate bonds with different ratings, attributing its more pronounced effect on riskier securities to rebalancing behaviors. Albertazzi, Becker and Boucinha (2016) study the transmission mechanism of the European Central Bank (ECB)'s Asset Purchase Program (APP) in euro area countries and validate importance of the portfolio rebalancing channel especially in more vulnerable countries. Gnabo and Soudant (2022) also point out the major role of the signaling and the portfolio rebalancing channels in the frameworks of conventional and unconventional policies in the Eurozone between 2003 and 2016.

Overall, while consensus has been reached about the *existence* of a portfolio rebalancing device, results about its *quantitative importance* are contradictory. This thesis explores the relationship between monetary policy, stock returns and rebalancing attitudes by certain investors, trying to clarify whether the latter has a significant role in the transmission of monetary policy impulses to financial markets. Specifically, it aims at answering three distinct but strongly interrelated questions:

1. What is the impact of monetary policy impulses on stock prices? In other words, what is the sensitivity of stock prices to monetary policy shocks?

2. What is the role of the portfolio rebalancing channel in the transmission mechanism of monetary policy?
3. Does the impact portfolio rebalancing mechanism triggered by monetary policy differ based on stock characteristics and, more specifically, between value and growth stocks?

The paper is organized in three main chapters, structured as follows. Chapter 1 deals with a general overview of the monetary policy transmission mechanism and the channels through which it is expected to affect the real economy, with a deeper focus on the portfolio rebalancing channel. In addition, it presents a simplified version of the rebalancing demand model laid down by Lu and Wu (2021) to define ex-ante expectations about the influence that the rebalancing device should theoretically exert on the stock market. Chapter 2 aims at answering question (1) only. The impact of monetary policy on equity prices is here examined through a structural vector autoregression with instrumental variables (SVAR-IV approach), using alternative measures of monetary shocks. Chapter 3 instead tries to quantify the role of rebalancing demand within the monetary policy transmission mechanism on value and growth stocks, thereby covering questions (2) and (3). Section 3.1, supplemented by various appendixes, describes the econometric framework and the data employed. Section 3.2 provides the baseline analyses for a sample of value and growth stocks using Nakamura and Steinsson (2018) high-frequency monetary policy shocks. Empirical findings from these analyses suggest that rebalancing demand has a negative but non-significant effect on the stock market; in response to a positive monetary policy shock, higher rebalancer ownership indeed leads to a downward revaluation of both value and growth stocks, which is however not significant in statistical terms. This result, initially derived in a basic model with just two regressors, also persists in better specified regressions, where a set of additional variables is introduced to control for potential contaminating effects. Section 3.3 present a series of alternative tests based on different inputs and modified data samples. Overall, alternative tests strengthen baseline results, again pointing to a negative but not significant impact of the portfolio rebalancing channel on the stock market; at the same time, they also reveal tendencies to rebalance *within* the stock market when certain kinds of policies are enforced.

Chapter 1
Monetary policy and portfolio rebalancing: an overview

1.1 The transmission mechanism of monetary policy

The transmission mechanism of monetary policy is a complex and manifold process working through a variety of different and interlaced channels. The standard approach in the literature distinguishes the latter into "primary" and "secondary" (or "amplification") channels; according to such classification, the portfolio rebalancing channel is generally placed within the former category. The multidimensionality that characterizes this transmission process allows real economy developments to be interpreted as the output of several intermediate steps: monetary policy affects the banking sector, asset prices, exchange rates and wages before showing its *real* impact. The introduction of unconventional monetary policy measures during the global financial crisis further affected this system, promoting new transmission channels while emphasizing the essentialness of some of the existing ones. According to Gnabo and Soudant (2022), the portfolio rebalancing and the signaling channels are those that, among the already established ones, contributed the most to the propagation of unconventional impulses – during and after the Great Recession.

In normal times, central banks pursuing an inflation targeting strategy implement conventional monetary policy (CMP) by controlling and altering their short-term policy rates.[2] Figure 1.1 provides a valuable summary of the entire CMP transmission mechanism, referring to its main direct and indirect effects. First, interest rate changes by the central bank alter agents' expectations about inflation and macroeconomic outlook *(signaling or expectation channel)* and influence shorter-term interest rates *(interest rate channel)*. In the framework of expansionary monetary policies – realized through policy rates' cuts - agents reasonably expect economic growth, higher inflation and lower unemployment; moreover, longer term rates – on the wave of the fall in shorter term ones – drop as well. These are immediate, "first layer" effects, commonly referred to as the "direct effects" of CMP. Direct effects then trigger a "waterfall process", affecting

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[2] The inflation targeting strategy, characterized by the choice of inflation as the intermediate target (nominal anchor) of monetary policy, is nowadays the most common strategy adopted by central banks. Inflation targeting emerged as a response to the practical failures of the monetary targeting strategy, widely diffused during 70s, that employed monetary aggregates as a nominal anchor.

asset prices *(asset pricing or portfolio rebalancing channel)*, bank lending rates *(bank-lending channel)* as well as the exchange rate *(exchange rate channel)*, whose variations are in turn reflected into changes in money demand, investments, wages and prices – as shown in Figure 1.1.

The portfolio rebalancing mechanism enters the process at the second layer of the chain, allowing the transmission of monetary policy impulses through financial markets and asset prices. A policy rates' cut drives lower yields on agents' original portfolios; some investors – the "rebalancers" – are therefore encouraged to revise their portfolio's composition, moving away from unprofitable money market securities toward riskier and more rewarding instruments, in a "search for yield" behavior (Oshima, 2020). Class, underlying features and maturity heavily shape an asset's risk profile: equities, real estate, corporate bonds and longer-term securities, all deemed as risky instruments due to their characteristics, therefore represent rebalancers' primary target during low rates phases. Contractionary monetary policies trigger the opposite effect: higher yields on safer assets attract investors, incentivizing them to transfer their positions away from risky securities.

The rise and fall in demand for alternative assets generate a sequence of price adjustments in the financial sector, shaping investments and inflation patterns. *Tobin's q* ratio usefully synthetizes such trends:

$$\text{Tobin's q} = \frac{\text{market value of assets}}{\text{replacement cost of assets}} \tag{1.1}$$

The numerator denotes the value of *new* financial (real) assets if issued (bought) at the current price; the denominator, instead, indicates the cost for a firm (consumer) to replace its *existing* assets. The magnitude of the numerator relative to the denominator determines the effects of monetary policy on investments. A *Tobin's q* higher than one shows that the market value of assets exceeds their replacement cost: in such case, it would be more convenient for a firm (a consumer) to issue (buy) new financial assets (real assets) rather than substituting existing ones; this stimulates investments, boosting inflation and economic growth. Contrarily, a *Tobin's q* lower than one suggests that firms and consumers would prefer to replace existing assets, reducing investments and depressing inflation and economic activity.

The portfolio rebalancing mechanism has been so far illustrated in relation to CMP. Interestingly, its functioning does not change when triggered by unconventional monetary policy (UMP) rather than CMP.[3] The most common, and

[3] The origin of UMP, as widely known, traces back to the outbreak of the Great Recession: the latter, indeed, proved the insufficiency of the inflation targeting strategy pursued through CMP to ensure price stability and financial soundness. With interbank rates stuck at the zero-lower bound (ZLB), no conventional monetary policy was effective anymore: this completely new

probably the most effective, unconventional tool employed by central banks since the beginning of the Global Financial Crisis (GFC) is quantitative easing (QE). Through quantitative easing programs, central banks free their balance sheets up from sizeable amounts of reserves, while replenishing them with private sector's assets, primarily bonds. Formally, QE interventions are structured as ordinary refinancing operations, with central banks providing liquidity to their counterparties in exchange for eligible assets. Their uniqueness stems from the magnitude of such purchases as well as from the type of securities sought by the central bank; indeed, these are risky securities, differently from the typical safe government bonds it usually acquires. Central banks' asset purchases activate the same portfolio rebalancing process described in relation to CMP: the massive flow of assets from private agents to the central bank leads to a scarcity of risky assets, noticeably reducing the return on the former's portfolios; liquidity, indeed, with zero nominal return, is not a perfect substitute for the instruments sold (Jakl, 2019). Attracted by positive returns, agents increase their demand for the few risky assets still available in the market, fueling their valuations and lowering their yield.

1.2 A model of rebalancing demand (Lu & Wu, 2021)

The model of rebalancing demand proposed by Lu and Wu (2021) provides an easy mean through which the theoretical notions laid down in chapter 1.1 could be illustrated in more concrete terms. In "Monetary Transmission and Portfolio Rebalancing: a Cross-Sectional Approach" (2021), the authors offer two alternative versions of the same model: the first, based on the idea of *instantaneous* rebalancing, assumes that agents rebalance their portfolios immediately after a monetary shock occurs; the second instead builds on the notion of *delayed* rebalancing, according to which investors revise their portfolios' composition at regular intervals (usually at the end of each quarter) only, independently from the timing of the shock. Under the simplification assumption that agents only rebalance instantaneously, this section just presents the first version of the model; consistently, the analyses in chapter 2 and 3 are also grounded on the same hypothesis.

"liquidity trap" or "ZLB" challenge forced central bankers to unwound innovative, "unconventional" monetary policy measures. More than ten years after the Great Recession, resorting to UMP is no more surprising. Rather, UMP formally entered central banks' monetary policy toolkit, with the joint purposes of safeguarding the transmission mechanism of monetary policy and addressing the ZLB issue.

1.2.1 Model assumption and setting

The model of instantaneous rebalancing by Lu and Wu (2021) relies on a set of four assumptions:

(1) There are only *two periods*: if a monetary shock occurs at time t, the period before t is identified as the "pre-shock period" while the period after as the "after-shock period";
(2) There are only *two stocks* in the market: stock 1 and stock 2;
(3) The behavior of just *two investors* is investigated: an equity arbitrageur and a rebalancer;
(4) *Rebalancing is instantaneous*: immediately after the monetary shock, the rebalancer alters the composition of his portfolio to meet a predefined target return.

Both stock 1 and 2 are dividend-paying assets, with dividend payouts being characterized by a bivariate Gaussian (normal) distribution, with the same mean μ and variance σ^2.

The mean vector and the variance-covariance matrix could be therefore written as:

$$\mu = [\,\overline{D}\ \overline{D}\,]' \qquad \Sigma = \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix}$$

where $\rho \in (0,1)$ denotes the correlation between the two stocks. The correlation is positive but lower than one; hence, the two stocks tend to comove without being perfect substitutes. Stock 1 and 2 also have the same pre-shock price $\overline{P}$, but differ in their post-shock price (P_1 and P_2) and in their investor base. Portfolios' composition is indeed as follows:

- The rebalancer holds only stock 1 plus some bonds;
- The equity arbitrageur does not hold bonds but invests in both stock 1 and 2.

Under these assumptions, the portfolio rebalancing model presented below aims at understanding how a monetary policy surprise at time t affects the return on the two stocks.[4] Such monetary surprise merely consists in a shock to the central bank's policy rate, with a direct influence on bond prices; depending on the nature of the shock – whether contractionary or expansionary – bond prices may revaluate upward or downward, leading to positive or negative bond returns. With B denoting a non-specific bond, the effect of a monetary policy shock is studied through its impact on B and its price.

A monetary tightening causes a fall in bond B's price, from $\overline{P_B}$ (bond B's pre-shock price) to P_B (bond B's post-shock price) leading to a negative return r_B:

[4] Later in the study, time t will denote the day of a monetary announcement by the Federal Open Market Committee (FOMC).

$$r_B = \frac{P_B - \overline{P_B}}{P} < 0 \qquad (1.2)$$

Reasonably, the bond revaluation spills over to the equity market, altering the price of both stocks:

$$r_1 = \frac{P_1 - \bar{P}}{\bar{P}} < 0 \text{ and } r_2 = \frac{P_2 - \bar{P}}{\bar{P}} < 0 \qquad (1.3)$$

with $r_1 \neq r_2$ given that $P_1 \neq P_2$; precisely, $|r_1| > |r_2|$.

Two aspects of the formulas in (1.3) should be emphasized. First, the *direction* of the price adjustments: the negative signs of r_1 and r_2 suggest that *both* stocks revaluate downward following a positive monetary policy shock, consistently with the view that restrictive policies generate a selling pressure in the whole equity market. The decline in the price of stock 1 – held by the arbitrageur as well as by the rebalancer – can be easily interpreted on the grounds of the discussion about the mechanism of rebalancing demand presented in the previous section: restrictive policies indeed encourage the rebalancer to shift away from risky assets, such as equities, and increase his positions in safe assets (bonds) to meet his pre-defined return target; the excess supply of stock 1 generated by the rebalancer therefore leads to a fall in its price ($P_1 < \bar{P}, r_1 < 0$). Since the rebalancer only increases the supply of stock 1 – the only one he holds within his portfolio – stock 2 might be thought to be exogenous to the entire rebalancing process. This, however, only holds under the assumption that two stocks are not correlated ($\rho = 0$); with a positive correlation between the two, as hypothesized before, rebalancing away from stock 1 affects stock 2 as well.

Second, the *scale* of the price adjustments: while both negative, the two returns indeed differ in terms of magnitude; specifically, the return gap $|r_1| - |r_2|$ is positive, signaling that the revaluation is more pronounced for stock 1 rather than for stock 2. Since the two assets are assumed to be identical except for their investor bases, the source of such difference can only be attributed to a portfolio rebalancing action.

To deeper examine the underlying causes of the two revaluations and the return gap between them, the following paragraphs detail the individual behaviors of each investor in response to a given monetary shock.

1.2.2 Arbitrageur's behavior

The equity arbitrageur chooses the original (pre-monetary shock) quantities of stock 1 and 2 – namely, Q_1^E and Q_2^E – to maximize his mean-variance utility function, given by:

$$\max_{Q^E} \left(Q_E\right)' \mu - \frac{\Gamma}{2}(Q_E)' \Sigma (Q_E) \qquad (1.4)$$

where $Q_E = \left[Q_1^E \, Q_2^E\right]' = \Gamma^{-1} \, \Sigma^{-1} \, \mu$ and $\Gamma > 0$ being a coefficient of risk aversion. The first order condition of (1.4) with respect to price yields the change in the quantity of each stock held by the arbitrageur following the monetary policy shock:

$$\begin{cases} \Delta Q_1^E = -\psi^d \, r_1 - \psi^s (r_1 - r_2) \\ \Delta Q_2^E = -\psi^d \, r_2 - \psi^s (r_1 - r_2) \end{cases} \quad (1.5)$$

where ψ^d is an "total demand" parameter, indicating the arbitrageur's magnitude within the equity market in terms of demand and ψ^s is a "substitutability" parameter. The latter captures the degree of substitutability between the two stocks and positively depends on the correlation coefficient ρ; the higher ρ, the easier for the equity arbitrageur to trade stock 1 for stock 2 and vice versa. In the simplest version of the model, both parameters are assumed to be strictly positive, i.e., $\psi^d > 0$ and $\psi^s > 0$; moreover, given that the arbitrageur is risk averse ($\Gamma > 0$), ψ^s is finite (there are limits to arbitrage between the two stocks). The first equation in (1.5) expresses the change in Q_1^E because of a monetary tightening as the sum of two components:

(1) The return on stock 1 itself (r_1), weighted by the parameter ψ^d;
(2) The return difference between the two stocks ($r_1 - r_2$), weighted by the parameter ψ^s.

The second equation, its mirror image, shows the change in Q_2^E following the same monetary shock.[5]

1.2.3 Rebalancer's behavior

Privileging diversification strategies, typical rebalancing institutions would never concentrate their investments in one asset class only. Consistent with this evidence, the rebalancer investor of this model invests a share w of his original wealth W^R in stock 1 only; the remaining portion $(1 - w)$ is instead invested in bonds. The parameter s is used to refer to the share of stock 1 he holds.

The change in rebalancer's original wealth due to a negative monetary shock at time t is the weighted average of the returns on stock 1 and bond B within the investor's portfolio:

$$\Delta W^R = wr_1 + (1 - w) \, r_B \quad (1.6)$$

[5] The minus sign before each component is obvious given that quantity and price move in opposite directions.

The change the quantity of stock 1 demanded by the rebalancer is then given by:

$$\Delta Q_1^R = s\,(\Delta W^R - r_1) = s\,(1-w)\,(r_B - r_1) \qquad (1.7)$$

1.2.4 Post-shock stock revaluation

Assuming that the number of shares issued for each stock does not change over a brief time window around the monetary announcement, the market clearing conditions could be written as:

$$\begin{cases} \Delta Q_1^E + \Delta Q_1^R = -\psi^d r_1 - \psi^s\,(r_1 - r_2) + s(1-w) = 0 \\ \Delta Q_2^E = -\psi^d r_2 - \psi^s (r_1 - r_2) = 0 \end{cases} \qquad (1.8)$$

By implementing the two equations above, stock returns are then found as:

$$r_1 = \frac{s\,(1-w)}{\Psi + s\,(1-w)} r_B \quad \text{and} \quad r_2 = \frac{\psi^d}{\psi^d + \psi^s} r_1 \qquad (1.9)$$

where $\Psi = \frac{\psi^d\left(\psi^d + 2\psi^s\right)}{\psi^d + \psi^s} \in (\psi^s, 2\psi^s)$.[6]

The first formula in (1.9) emphasizes the importance of w and s for the magnitude of r_1:

- The lower w, the higher r_1; with a higher bond fraction, the portfolio value shrinks more in response to a restrictive monetary policy shock. This generates a higher selling pressure from the rebalancer, resulting in a higher downward revaluation of stock 1;
- The higher s – thus, the more stock 1 is held by the rebalancer rather than by the arbitrageur – the more stock 1 reacts to the monetary shock, and the higher the gap between r_1 and r_2.

In addition, the second formula in (1.9) shows that also stock 2, despite being held by the arbitrageur only, is subject to a revaluation. Under the assumption that $\psi^s > 0$, however, $|r_1| > |r_2|$: stock 1, held by both the arbitrageur and the rebalancer, reacts more to a monetary shock compared to stock 2, held solely by the arbitrageur. The size of the return gap depends on the degree of arbitrage

[6] Appendix A from Lu and Wu (2021) details the specific procedure to retrieve r_1 and r_2. They first find r_2 by implementing the second market clearing condition; then, they find the return gap $(r_2 - r_1)$ by taking the difference between the two market clearing conditions in (1.8); finally, they combine results obtained in the previous two steps to come up with return r_1.

between the two stocks: the more the two stocks can be substituted, the closer their revaluations and the smaller the return gap. When not substitutable ($\psi^s = 0$), stock 2 does not experience any downward revaluation; the return gap will therefore be maximum.

Finally, under the assumption that the equity universe counts stock 1 and 2 only (in section 1.2.1), the stock market revaluates, at the aggregate level, by the average of the two returns:

$$r_M = \frac{r_1 + r_2}{2} \tag{1.10}$$

Chapter 2
Stock return sensitivity to monetary shocks

Figure 1.1 provides the intuition that, through its transmission system, monetary policy decisions effectively influence financial markets and the real economy. Empirical evidence only partially supports this idea; discrepancies in the results obtained by employing different inputs or econometric models, indeed, do not allow to make univocal inference about their relationship and to adequately quantify their relevance. Most studies, however, agree on the *procedure* to measure the sensitivity of economic and financial variables to monetary policy. Specifically, traditional methodologies are grounded on two pillars: first, the derivation of high-frequency monetary policy shocks as a numerical measure of the information contained in central banks' announcements; second, the application of structural vector autoregressions (SVAR) as the main estimation models. With matching approaches, heterogenous outcomes are largely explained by differences in the strategy adopted to measure shocks and to deal with the impossibility of directly estimating SVAR models.

Following the most recent literature, this chapter implements a SVAR-IV approach to derive the effect of (one standard deviation) monetary policy shock on stock excess returns. Section 2.1 outlines the main theoretical notions about SVAR and the external instrument approach as a tool to overcome the SVAR identification issue. Section 2.2 then presents empirical results based on two distinct sets of monetary surprises, to understand how they are affected by different shock estimation techniques.

2.1 A review of SVAR and impulse response functions

2.1.1 The SVAR identification problem

Time series analysis allow to examine the evolution of variables over time, to detect trends and patterns in their behaviors and to ultimately derive reliable forecasts about their progression. In Kirchgässner, Wolters & Hassler (2012) time series analysis is indeed viewed as the mean through which "laws" in variables' dynamics could be derived and exploited to "predict their future developments".[7]

[7] According to Tsay (2000), time series and forecasting analysis may have different objectives; often, however, time series analysis has forecasting as its primary goal.

Vector autoregression (VAR) models are usually categorized into "structural" and "reduced form" models. While different in their functional form, they are deeply interconnected; the following paragraphs investigate such relationship starting from a simple first order reduced form VAR.
A reduced form VAR of order 1 (p = 1) has the following form:

$$y_t = A(L)y_{t-1} + u_t \qquad (2.1)$$

where – according to the notation provided by Cesa-Bianchi (2022):

- y_t is a *K x 1* "state vector" of *K* (economic) endogenous variables, whose relationship is the object of study;
- *A (L)* is a *K x K* "dynamic matrix" describing the effect of lagged endogenous variables on the endogenous variables themselves at time *t*, with *L* being the lag operator;
- u_t is a *K x 1* vector of reduced form shocks (errors).

The link between structural and reduced form VARs is "hidden" within u_t . With ε_t indicating a *K x 1* vector of unobservable structural shocks, i.e., shocks to the endogenous variables in y_t, and *B* being a *K x K* "impact matrix" (Lakdawala, 2017), the vector u_t can indeed be expressed as a linear combination of entries in ε_t :

$$u_t = B\varepsilon_t \qquad (2.2)$$

Consequently, model (2.1) can be rewritten in terms of structural shocks as:

$$y_t = A(L)y_{t-1} + B\varepsilon_t \qquad (2.3)$$

Coefficients in *B*, called "structural parameters", describe the impact of a structural shock on output variables in y_t; in the economic language, they are labelled as "impulse response functions" (IRFs). While pivotal in most analyses, structural shocks, as anticipated above, are unobservable. That being the case, it is not feasible to *directly* estimate a SVAR model; only indirect methods working through a first-step estimation of reduced form shocks allow to consistently estimate structural parameters in *B*.
At first sight, the formulation of reduced form shocks in (2.2) and (2.3) might (wrongly) suggest that there exists a one-to-one relationship between structural and reduced form shocks. In such hypothetical scenario, a structural shock to the *i*-th endogenous variable would be responsible of the *i*-th reduced form shock only; an extensive formulation of (2.3) clarifies the unlikeliness of such circumstance.

In the easiest scenario with two endogenous variables only, i.e., $y_t = [y_{1,t}\ y_{2,t}]'$, model (2.3) becomes:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \qquad (2.4)$$

Reduced form shocks can then be derived from (2.4) as:

$$\begin{cases} u_{1,t} = b_{11}\varepsilon_{1,t} + b_{12}\varepsilon_{2,t} \\ u_{2,t} = b_{21}\varepsilon_{1,t} + b_{22}\varepsilon_{2,t} \end{cases} \qquad (2.5)$$

As linear combinations of *multiple* structural shocks, there is no one-to-one relationship between a reduced form shock to variable i and a structural shock to the same variable i. Such possibility is contemplated only if the reduced form shock to variable i itself is not sensitive to a structural shock in variable j (for all $j \neq i$), i.e., the coefficient b_{ij} in (2.5) equals zero. The inability to disentangle the effect of each individual structural shock on reduced form ones, if not under the previous assumption, leads to the so-called "SVAR identification problem".

However, while estimating reduced form shocks does not allow to directly retrieve structural parameters in B, properties of reduced form shocks themselves offer a nice workaround to the SVAR identification issue. As dependent on those of structural shocks, the latter's features are listed first. Specifically, they include:

1. *Mean independence*: structural shocks have mean zero, i.e., $E(\varepsilon_t) = 0$;
2. *Orthogonality among contemporaneous shocks*: there is no correlation among contemporaneous structural shocks, i.e., $Cov\ (\varepsilon_{i,t}, \varepsilon_{j,t}) = 0$ for all $j \neq i$;
3. *No serial correlation*: structural shocks have a constant variance over time. With t and s indexing periods, $Var\ (\varepsilon_{i,t}) = Var\ (\varepsilon_{i,t+s}) = \sigma$ for all $s \neq t$.

By combining assumptions (2) and (3), the variance/covariance matrix of structural shocks (Σ_ε) has the following structure:

$$\Sigma_\varepsilon = \begin{bmatrix} \sigma_1^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_K^2 \end{bmatrix} \qquad (2.6)$$

where σ_1^2 is the variance of the i-th structural shock and the zero off-diagonal elements indicate uncorrelation among contemporaneous structural shocks. By normalizing the latter to a constant variance of 1, Σ_ε becomes an identity matrix (I). Accordingly, structural errors are normally distributed with mean zero and a variance-covariance matrix I:

$$\varepsilon_t \sim N\ (0, I) \qquad 2.7)$$

Given that $u_t = B\varepsilon_t$ as per (2.2), the variance-covariance matrix of reduced form shocks, denoted by Σ_u[8], equals to:

$$\Sigma_u = E(u_t u_t'') = BB' \qquad (2.8)$$

Formula (2.8) translates into:

(1) *Eventual cross-correlation among reduced form shocks*: since the coefficients outside the main diagonal in the covariance matrix Σ_u can be potentially different from zero, the assumed uncorrelation among structural shocks does not translate into uncorrelated reduced form shocks;

(2) *Restatement of the SVAR identification problem*: the original issue indeed boils down to finding an impact matrix B that satisfies $\Sigma_u = BB'$.

Despite (2) makes the SVAR identification problem easier to interpret, providing it with a solution is still cumbersome: infinite combinations of parameters in B indeed allow the equation $\Sigma_u = BB'$ to be satisfied. Otherwise stated, structural parameters are still "unidentified" (Gottschalk, 2001).

Different methods have been pinned down to overcome the SVAR identification problem. Traditional techniques are based on "restrictions" – that is, additional equations imposed to the model to allow for a unique solution to equation $\Sigma_u = BB'$. In this respect, the Cholesky decomposition or "zero short-run restrictions" is one of the most common methods. More modern studies (Nakamura & Steinsson, 2018; Olea, Stock & Watson, 2021; Lu & Wu, 2021) instead employ "external instruments" to identify structural shocks of interest. The latter is described in more details below.

2.1.2 Identification through external instruments

The external instruments' identification approach is grounded on the use of instrumental variables as *proxies* for the unobservable structural shock of interest.[9] Later in the section, the structural shock of interest will be defined as the monetary policy shock, i.e., a shock to the monetary policy indicator. Notation is as follows:

- ε_t is a $K \times 1$ vector of structural shocks at time t, with ε_t^i denoting the structural shock of interest and ε_t^j, for all $j \neq i$, denoting all other structural shocks;
- Z_t denotes the instrumental variable for the structural shock of interest ε_t^i at time t.

A "good" instrument Z_t is a variable "external" to the VAR system, i.e., not contained in the state vector, which satisfies two fundamental conditions:

[8] Derivation: $\Omega = E(u_t u_t') = E(B\varepsilon_t \varepsilon_t' B') = BE(\varepsilon_t \varepsilon_t')B' = BIB' = BB'$.

[9] For this reason, this identification scheme is commonly known as "*proxy SVAR*".

(1) *Relevance*: it is correlated with the structural shock of interest. Hence:

$$E(Z_t \varepsilon_t^{j'}) = \Phi \neq 0 \qquad (2.9)$$

(2) *Exogeneity (validity)*: it is not correlated with structural shocks other than the structural shock of interest. Hence:

$$E(Z_t \varepsilon_t^{j'}) = 0 \qquad (2.10)$$

Based on (2.9) and (2.10), the covariance between reduced form error u_t and Z_t becomes:

$$E\,(Z_t\, u_t^{'}) = E\,(Z_t \varepsilon_t B) = \Psi = \Phi b_1 \qquad (2.11)$$

Once a set of instrumental variables satisfying the relevance and validity conditions has been identified, the SVAR-IV approach merely turns into a two-stages least square regression, as follows:

1. *First stage regression*: reduced form residuals of the regression of interest (u_t^i) are regressed on the chosen instrument (Z_t) to derive fitted values $\widehat{u_t^i}$. The latter represents the projection of reduced form residuals of interest on the instrument, i.e., the component of the endogenous variable of interest which is left unexplained by VAR, and which can be instead explained by the instrument.

$$u_t^i = \gamma_0 + \gamma_0 Z_t + \epsilon_t \qquad (2.12)$$

2. *Second stage regression*: u_t^j for all $j \neq i$ is regressed on fitted values $\widehat{u_t^i}$ derived in the first stage. The effect of a monetary policy shock on variable j, for $j \neq i$, is therefore derived by means of its impact on variable i.

$$u_t^j = \beta_0 + \beta_1 \widehat{u_t^i} + \eta_t \qquad (2.13)$$

2.2 Measuring stock returns' sensitivity to monetary shocks

2.2.1 Data and methodology

Following Lu and Wu (2021), the structural VAR set up to study the relationship between monetary shocks and stock returns is characterized by six variables and six lags. The 6-dimensional state vector is defined as:

$$y_t = [y_{1,t}\ y_{2,t}\ y_{3,t}\ y_{4,t}\ y_{5,t}\ y_{6,t}]'$$

where $y_{1,t}$ denotes the one-year Treasury yield in month *t*, $y_{2,t}$ denotes the relative bill rate in month *t*, $y_{3,t}$ denotes the smoothed dividend price ratio in month *t*, $y_{4,t}$ denotes the excess equity return (S&P 500 return relative to the 1-month T-bill rate) in month *t*, $y_{5,t}$ denotes the natural logarithm of the consumer price index (CPI) in month *t*, $y_{6,t}$ denotes the natural logarithm of industrial production in month *t*.

The one-year Treasury yield is chosen as the *monetary policy indicator;* it is set as the first element of the state vector for convenience. Coherently, *monetary policy shocks* should be intended as shocks to the monetary policy indicator. As Gertler and Karadi (2015) point out, the monetary policy indicator must be distinguished from the monetary policy *instrument* employed by Federal Reserve: the latter is the Federal Funds rate – that is, the *short-term rate* at which credit institutions exchange excess reserves overnight in the interbank market; the former is instead a *longer-term* rate, being it the yield on Treasury securities with maturity one year. The choice of a longer-term rate is justified by the intention to capture both policy rate shocks, i.e., shocks to the current federal funds rate, as well as forward guidance shocks, i.e., shocks to future rates. Importantly, innovations to the monetary policy indicator might be therefore caused by either policy rate or forward guidance shocks or, more likely, by their joint effect.

The external instruments approach primarily revolves around the choice of a monetary policy surprise measure to be used as an instrument. Here, two sets of monthly monetary policy shocks are selected:

1. Gertler and Karadi (2015) surprises (January 1990-July 2012)
2. Romer and Romer (2004) surprises (July 1979-December 2007 and July 1979-July 2012)

These two measures crucially differ in their computation technique. On the one hand, Gertler and Karadi (2015)'s estimate of policy shocks is derived as the unexpected changes in the federal funds futures rate in subsequent quarters. On the other, Romer and Romer (2004) measure monetary shocks as the difference between *predicted* and o*bserved* changes in federal funds rate before and after a FOMC meeting, obtaining the former from Greenbook forecasts – a set of forecasts about inflation, output, and unemployment – prepared by Fed economists for the Committee. The discussion about these two measures of monetary policy surprises is widened in chapter 3.1 with reference to high-frequency monetary surprises; monthly shocks here employed simply result from their aggregation.

Data related to economic and financial variables as well as to Gertler and Karadi (2015) monetary policy shocks are taken from the dataset used by Kekre and Lenel (2022) in "Monetary policy, Redistribution and Risk premia" (2022). The dataset contains the relevant figures at monthly frequency over a sample spanning from 1979 to 2012. With respect to Romer and Romer (2004) shocks, the updated version by Wieland and Yang (2019) is employed. They present two distinct measures of monthly shocks by estimating Romer and Romer (2004) regression twice: the first is based on a sample spanning from July 1979 to December 2007; in the second regression, the sample is extended to July 2012. Both series are used in the SVAR-IV analysis, denoted as "short-sample" and "long sample" Romer-Romer (2004) surprises respectively.

Over the time window covered by all of them (January 1990-December 2007), the correlation between Gertler and Karadi (2015) and Romer and Romer (2004) shocks is positive but extremely low; this inevitably increases the likelihood of remarkable differences in the impact of the two series on the economic variables in y_t. As expected, instead, the correlation between short sample and long sample Romer and Romer (2004) shocks is almost close to one. Table 2.1 reports the matrix with specific correlation values.

All shocks are normalized to a unit standard deviation; impulse response functions can be therefore interpreted as the output's reaction to a one-unit standard deviation monetary policy shock as in Gertler and Karadi (2015), Lu and Wu (2021) and Kekre and Lenel (2022).

2.2.2 Empirical results

The analytical procedure implemented builds upon the external instruments approach explained above. In a first step, a sixth order reduced form VAR with six independent variables is estimated for each endogenous variable in the state vector. For each of them, including the regression of interest, reduced form residuals are derived; given the six lags, the vector of reduced form residuals has length $N - 6$, with N denoting the number observations for each variable in y_t.[10] Then, a two-stages least squares regression is replicated three times with the help of each external instrument.

In the first-stage regression, residuals from the Treasury yield regression $(u_{1,t})$ are predicted by instrumental variables (Z_t). Table 2.2 summarizes the results related to beta coefficients (sign, magnitude and p-value) and the F-statistics associated to each regression. First-stage regression using Gertler and Karadi (2015) surprises yields a beta coefficient of 0.0465, with an F-statistic of 11.71. With Romer and Romer (2004) shocks, the first stage beta equals 0.1767 and 0.1692 when the series is derived using the short and the long sample respectively. F-statistics are equal to 81.02 and 72.87 respectively.

The interpretation of such beta coefficients is straightforward: as elements of the impact matrix B, they represent the response of the reduced form residuals of the one-year Treasury yield regression to monetary policy shocks. Despite the

[10] Overall, the residual matrix has dimension $(N-6) \times 6$.

effect is always positive, a substantial difference between Gertler and Karadi (2015) and Romer and Romer (2004) shocks can be noticed: when the latter is employed (columns 2 and 3), the impact of monetary surprises on the monetary policy indicator appears to be far more relevant.

The unbiasedness of the beta estimators reported in Table 2.2 is heavily conditional on the exogeneity and the relevance of the instruments employed. Relevance can be immediately assessed by checking the F-statistics associated to each first stage regression. The higher the first-stage F-statistic, the stronger the instrument; according to the most conservative rule of thumb provided by Staiger and Stock (as cited in Stock and Yogo, 2002), whenever the first-stage F-statistic is below 10, the instrument should be considered “weak”. Following such rule, all instruments in the analysis are relatively strong, as all F-statistics are well above the threshold: however, the appreciable gap between their values in Romer and Romer (2004) and Gertler and Karadi (2015) regressions suggests that the former shocks are stronger instruments.

The second-stage regression, estimated as per (2.13) by projecting residuals of other five regressions on predicted values from (2.12), allows for the impact of a monetary policy shock on the other five economic variables in the state vector to be interpreted through the lens of the monetary policy indicator (Kekre and Lenel, 2022). Table 2.3 reports the results for the excess stock return regression.

A positive one standard deviation Gertler and Karadi (2015) monetary policy shock causes stock returns to fall by roughly 8 percentage points (pp). Such decrease is quite high, especially if compared with results derived from the other two regressions: a positive short sample Romer and Romer (2004) monetary shock implies 0.53 pp lower returns only; a positive long sample Romer and Romer (2004) shock is instead responsible of 1.78 pp drop in equity returns, not far from 1.9 pp value estimated by Kekre and Lenel (2022). Despite the differences in the magnitude of the decline, all analyses coherently predict that contractionary monetary policies lower equity returns; the very high p-values, however, testify that this effect is never significant. The effect of the two Romer and Romer (2004) shock series is quite different – both in terms of coefficients and related p-values; this is rather surprising, given that their correlation is almost close to one.

Figures 2.4.1, 2.4.2 and 2.4.3 plot impulse response functions of the one-year Treasury yield (monetary policy indicator) and excess stock return using the three different sets of monetary policy shocks.[11]

[11] Plots of impulse response functions are retrieved through Cesa-Bianchi (2022) Matlab codes.

Chapter 3
Portfolio rebalancing: empirical evidence from US stocks

This chapter presents the empirical results from a range of analyses aimed at quantifying the effect of the portfolio rebalancing channel on the equity market. Chapter 2 provided evidence on the relationship between monetary policy and stock returns, showing that the former affects, even if not significantly, equity valuations; a more detailed examination of the monetary policy transmission mechanism places the attention on whether – and in which proportion – this effect could be attributed to a portfolio rebalancing process.
The first paragraph describes the samples, the variables and the methodology employed in the analyses, with theoretical backgrounds to motivate the specific choices made. The second section presents the results from the main assessment carried out on two distinct samples, namely samples of "value and "growth" stocks. Finally, the third section offers a set of alternative tests to explore more in depth the portfolio rebalancing mechanism under certain policies and during the global financial crisis.

3.1. Data and methodology

3.1.1 Samples

Two distinct and independent samples of US companies, equal in size but different in their composition, are employed. Specifically:

- A sample of value stocks ("NYSE sample"), made of 57 US-incorporated companies included in NYSE Composite Index;
- A sample of growth stocks ("NASDAQ sample"), made of 57 US-incorporated companies included NASDAQ-100 Index.

Non negligible difficulties arise in properly recognizing value and growth stocks due to the several dimensions along which they can be classified. Haitsma, Unalmis and de Haan (2015) distinguish value and growth stocks based on their book-to-market and price-to-earnings ratios, with value (growth) stocks being characterized by high (low) book-to-market ratios and low (high) price-to-earnings ratios. In Table 3.1 (a) univariate analyses of book-to-market ratios show that the mean value for NYSE sample (1.77) is far higher than that of NASDAQ stocks (0.36), providing evidence in favor of the above classification. This result also holds at the annual level: as shown in Table 3.2, NYSE stocks enjoy higher book-to-market ratios every year in the sample.[12]

Cash flow (equity) duration, i.e., sensitivity of cash flows to interest rates, also contributes to such categorization. Value stocks generally exhibit lower equity durations since they yield earlier cash flows, being thus less sensitive to discount rate's fluctuations. Equity duration is here computed following Dechow, Sloan and Soliman (2004); the detailed procedure is provided in Appendix C. Table 3.1 (c) shows that NYSE stocks have a mean equity duration of 22.86 years, compared to the 23.22 years of NASDAQ stocks. Such difference, despite not substantial, still supports the classification of NYSE (NASDAQ) stocks as value (growth) stocks. Yearly duration values are a bit surprising; for seven out of fifteen years, indeed, value stocks show higher durations compared to growth stocks, as Table 3.3 points out. However, considering the multitude of factors that may affect yearly measures – the number of missing data each year above all – they are legitimately disregarded in favor of the more comprehensive evidence offered by Table 3.1 (c).[13]

Besides equity duration and book-to-market ratio, the nature of a firm's business may also help to identify it as a value or growth stock. In this respect, technology and innovation-based firms are typically the best candidates to be growth stocks; contrarily, companies in more conservative industries and with already well-established cash flows generally fall within the value category. Table 3.3 (a) and (b) provide a detailed list of each company's industry group for each sample, proving that, while NASDAQ sample is mostly made of growth companies, NYSE sample's firms mainly belong to "traditional" industries. [14]

The time window chosen for the analysis counts 15 years from January 2000 to December 2015. For variables whose calculation is conditional on current as well as on previous periods data, the sample is extended to 20 years with January 1995 as the starting month.

Companies are identified through their North American Industry Classification Standard (NAICS) code, a six-digits numeric code that allows to frame a firm from the sector to the national industry it belongs to. NAICS is here adopted in place of

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[12] Table 3.1 (b) also shows univariate analyses in terms of market capitalization; consistently with the expectations, value stocks have a lower market value of equity compared to growth stocks.

[13] Moreover, Dechow, Sloan and Soliman (2004) find that book-to-market ratio could be employed as a "crude proxy" for duration: usually, stocks with a high book-to-market ratio enjoy lower durations and vice versa. Given that duration values are heavily dependent on the parameters chosen, stocks with a high book-to-market ratios could be reasonably assumed to have low durations and vice versa.

[14] The appreciable degree of heterogeneity between the two samples in terms of firms' core features –book-to-market ratio, equity duration and industry group – is not incidental; rather, it is deliberately sought to differentiate the role of rebalancing demand across stocks, allowing for potential comparisons among the outcomes.

the Standard Industry Classification (SIC), employed by most authors, considering that it replaced the latter in 1997 as the reference classification criterion. Firms are distinguished according to their *industry group*, as standard in the literature; while in SIC this can be figured out through the first three numbers of the code only, NAICS also requires the fourth one to be considered. Such clustering approach – based on industry group rather than on sector – helps to distinguish companies in terms of their individual business, thereby eliminating potential return differences among firms belonging to the same sector but different industries. Figure 3.4 (a) and (b) show the sector composition of each sample; a comparison with Table 3.2 (a) and (b) allows to immediately notice *within-sector* differences (in terms of industry groups) between the two samples.[15]

3.1.2 Panel data model and variables

To assess the impact of the rebalancing demand on stock returns, the following model is estimated:

$$r_{i,t} = \beta_0 + \beta_1 RO_{i,t} + \beta_2 RO_{i,t}\, x\, MS_t + \beta_3 Controls_{i,t} + \beta_4 Controls_{i,t}\, x\, MS_t + \delta_t + \varepsilon_t \tag{3.1}$$

where the subscripts *i* and *t* denote the firm and the time index respectively. More specifically, *t* indexes the *days of interest*; hence, day *t* is the FOMC's meeting day.[16] Here the list of the variables included in the model:

- $r_{i,t}$ is the daily return of firm *i* on day *t;*
- MS_t is a measure of high-frequency monetary shock on day *t;*
- $RO_{i,t}$ denotes the percentage of rebalancer ownership of firm *i* on day *t – 1,* i.e., the percentage of traded shares held by institutions classified as "rebalancers" the day *before* the FOMC meeting;
- $Controls_{i,t}$ is a matrix of control variables, each one for firm *i* on day *t;*
- δ_t is a set of fixed effects (time and industry fixed effects);
- ε_t denotes the error term of the fixed-effects regression.

Data on prices, rebalancer ownership and control variables are taken from Thomson Reuters database for the period January 2000-December 2015, with some exceptions in case a longer time span (starting from January 1995) is

[15] As an example, Ametek, Glatfer Corporation and Ingredion – included in NYSE sample – all belong to the manufacturing sector but to different industry groups. The former produces navigational and electromedical devices; the second and the third are in the paper and in the food industry, respectively.

[16] Day *t* only refers to *scheduled* FOMC meetings, organized eight times per year; emergencies and extraordinary situations may also require *unscheduled* meetings to be arranged (ex: those arranged on 13/09/2001 and 17/09/2001, just after the Twin Towers attack), but they are not considered in the sample.

required; monetary shocks come from Nakamura and Steinsson (2018) series as updated by Acosta (2022).[17] The following paragraphs just provide a brief description of the above-mentioned variables; more extensive explanations can be found in Appendixes B and C.

Daily returns

Stock returns used as the outcome variable are computed at a daily level as:

$$r_{i,t} = ln\ (P_{i,\ t}/P_{i,\ t-1}) \qquad (3.2)$$

where $P_{i,t}$ is the closing price of stock i on the FOMC announcement day and $P_{i,t-1}$ is firm i's closing stock price the day before. Lu and Wu (2021) employ *intraday* equity returns around FOMC meetings thanks to the considerable data granularity offered by the Trade and Quote Database (TAQ).[18] Thomson Reuters, however, does not provide intraday stock prices series: daily prices, through which a sufficiently accurate measure of return could still be found, are therefore used.[19]

Missing prices are not copious considering the extension of the period; leaving these "holes" would therefore not represent a major shortcoming in the study. However, some manual adjustments have been made based on the system Thomson Reuters adopts to display data; specifically, if the price for the selected date is not available, it reports the price of the nearest days available. Accordingly, if the price *on* the FOMC date is not available, the *next* available price is employed; if the price on the day *before* the FOMC date misses, the *last* available price is instead used as its proxy.[20]

[17] Acosta (2022) reproduces Nakamura and Steinsson (2018) shocks in case of scheduled meetings; the original Nakamura and Steinsson (2018) sample comprises unscheduled meetings as well, but it is shorter than that under analysis (it ends in March 2014) and bypasses the apex of the financial crisis (second half of 2008 and first half 2009). This explains why t only indexes scheduled meetings' dates.

[18] Nakamura and Steinsson (2018) use an estimation window of 30 minutes: given that FOMC meetings usually occur at 14:15, they compute intraday return taking the last trading price more than ten minutes before the meeting (before 14.05) and more than ten minutes after (after 14:35).

[19] This approach is justified by the fact that FOMC meetings generally occur around 14:15 – hence before US stock exchange close, at 16:00; it is thus reasonable to assume the closing price on the same day of the meeting (rather than the day after) as the post-announcement price.

[20] An example of such manual adjustments: the Old Dominion Freight Line – in NASDAQ sample – misses on the day before FOMC date 21/08/2001; the last available price – provided for 17/08/2001 – is used to calculate return.

High-frequency monetary shocks

As pointed out by Barakchian and Crowe (2010), *simultaneity* represents the major identification problem when measuring the impact of monetary policy on financial markets and economic activity. What is the direction of causality between monetary policy and the status of the economy? Does monetary policy *act on* the economy or does it *react to* the economy? The literature agrees on the answer: the "action" and the "reaction" channels of monetary policy work together. Inevitably, financial markets and real economy's responses to monetary policy announcements have two interrelated components (Zhang, 2021); the reaction stemming from changes in monetary policy stance is indeed combined with a response component related to the economic environment.

When examining the transmission mechanism of monetary policy, the focus must be placed on the *action* component of central banks' decisions; otherwise stated, only monetary policy changes that do not follow from economic evolutions must be inspected. Such component is quantified through monetary policy shocks, i.e., the *unexpected* component of policy changes. Bauer and Swanson (2022) concretely visualize monetary policy shocks through the following reaction function:

$$i_t = f(X_t) + \varepsilon_t \qquad (3.3)$$

where:

- i_t is the policy rate set by the central bank at time t, with an indirect influence on financial markets;
- X_t is a $N \, x \, K$ matrix with K denoting a set of variables describing the status of the economy at time t, such as GDP, unemployment rate and inflation;
- f is the Fed's policy rule or monetary policy stance, i.e., how the Fed responds to X_t;
- ε_t is an exogenous monetary policy shock, i.e., an exogenous deviation from the Fed's policy rule f.

A deviation of the policy rate i_t from the private sector ex-ante (at $t - 1$) expectations about i_t itself, conditional on all available information at time $t - 1$:

$$i_t - E_{t-1}(i_t | I_{t-1}) \qquad (3.4)$$

might have three sources:

1. An "exogenous monetary policy shock" ε_t;
2. A "Fed information effect" (Nakamura & Steinsson, 2018; Acosta, 2022), caused by *asymmetric information* about the status of the economy (X_t) between the central bank and the private sector;

3. A "Fed response to news effect" (Bauer & Swanson 2022), attributable to the divergence between the actual central bank's policy rule *f* and the private sector's expectations (at $t-1$) about *f*, as well as to the effect of *new information* on *f* itself.

Informational issues explain both (2) and (3) in different ways. The Fed information effect attributes policy rate surprises to an informational gap between the central bank and private agents, which leads to forecast revisions about the status of the economy by private agents only. Monetary policy decisions are indeed the by-product of the central bank's *own view* about the economic outlook; whether the private sector has a disagreeing representation of the economic reality, however, it will revise its expectations based on the monetary actions enforced. For example, a fall in policy rates, fostering the belief of a weak economy, leads private agents to forecast higher inflation and lower GDP.

On the other hand, the Fed response to news effect argues that a monetary policy surprise is generated when the actual reaction of the central bank (*f*) to the business cycle (X_t) differs from the private sector's ex-ante expectations about it; a positive shock might originate, for example, from policy rates' cuts less marked than expected. Bauer and Swanson (2022) investigate the source of this mismatch in the set of economic news released *before* the FOMC meeting but after the publication of market participants' macro forecasts; the timing of such news releases causes latest information to be incorporated in the Fed's announcement only, without shaping private agents' expectations.

Identification issues arise since policy rate changes are a *composite* output of the three effects. Albeit with different contributions and weights, all three channels play a role in generating the final surprise. In view of understanding the impact of monetary policy on asset prices, it is however key to disentangle their individual impacts, placing the attention on the exogenous component of the aggregate shocks only.

The most used measures of high-frequency shocks come under the name of "traditional measures" of monetary shocks; following Acosta (2022), these comprise "market based" and Romer and Romer (2004) shocks. They will be employed in this paper as well. Specifically, the baseline study in section 3.2 makes use of Nakamura and Steinsson (2018) high-frequency shocks updated by Acosta (2022); section 3.3 will lever on both Nakamura and Steinsson (2018) surprises and Gürkaynak, Sack and Swanson (2005) – henceforth "GSS" (2005) – target and path factors, again supplied by Acosta (2022).[21]

[21] It must be pointed out that traditional measures of monetary shocks are not free of biases. One of the most crucial issues relates to the evidence that such shocks may suffer from serial correlation; such feature inevitably impacts the validity and the reliability of the measure. With the goal of overcoming such drawbacks, more recent methodologies led to the development of other, "new" measures of shocks; relevant examples include Miranda-Agrippino and Ricco (2017) and Acosta (2022) surprises.

Traditional market-based measures are obtained from changes in market expectations of federal funds futures rates, differing only in the number and the type of contracts considered. Federal funds futures are monthly contracts traded on the Chicago Mercantile Exchange (CME) whose rate – the "federal funds futures rate" (*FFFR*) – is set as the average of the daily effective federal funds rates (*EFFR*) of the month of the contract itself (Robertson & Thornton, 1997).[22] Using Robertson and Thornton (1997) notation, the relationship between the *FFFR* and the *EFFR* could be written as:

$$FFFR_{t,i} = E_t\overline{EFFR}_{t+i} + \alpha_i \qquad (3.5)$$

where t and i indicate months and $i > t$ (month i is later in time with respect to month t), E_t denotes the conditional expectation and α_i is a "bias term".

Breaking down equation (3.5), it is clear that – absent any bias α_i – market expectations in month t about *EFFR* in month i equal the i-month ahead *FFFR* $(FFFR_{t,i})$. Reversing the two sides of the equation, the $FFFR_{t,i}$ is interpreted as a predictor of market expectations in month t (that, in this case, is the month in which a FOMC announcement is made) about $\overline{EFFR}_{t+i}$. Accordingly, *changes* in the federal funds futures rate could be interpreted as proxies for changes market expectations of the federal funds rate, i.e., they are proxies for monetary policy shocks.

Kuttner (as cited by Acosta, 2022) just refers to changes in the *current month* federal funds futures rate as predictors of changes in the federal funds rate; Gertler and Karadi (2015) instead employ changes in *farther* ahead federal funds futures rates; finally, other authors such as GSS (2005) and Nakamura and Steinsson (2018) combine several federal funds and Eurodollar futures rates to come up with a shock measure. Specifically, they consider the following five variables:

- Change in market expectations about federal funds rate over the remainder of month t (FOMC announcement month);
- Change in market expectations about federal funds rate in $t + 1$ (month in which the next scheduled FOMC meeting will take place);
- Change in price of three Eurodollar futures, with different expiration dates, in month t:
    - Change in price of Eurodollar futures expiring in 2 quarters;
    - Change in price of Eurodollar futures expiring in 3 quarters;
    - Change in price of Eurodollar futures expiring in 4 quarters.

[22] The daily effective federal funds rate is a volume-weighted median of all daily transactions from depository institutions in the FR 2420 Report (Federal Reserve Bank of New York, 2023). It is published every day by the Federal Reserve Bank of New York.

Both GSS (2005) and Nakamura and Steinsson (2018) then apply Principal Component Analysis (PCA) to extract information from data and build the final shocks; the main aspects of PCA are summarized in Appendix A.

GSS (2005) employ PCA to compute a “target” and a “path” factor of the monetary surprise. The target factor – that is, the first principal component (PC1) of the five variables considered – isolates the component of the shock that affects the *current target* for federal funds rate. Consequently, it must be through as a “policy rate shock”. The path factor – computed as the second principal component (PC2) – instead consists of the shock to *future* federal funds rates, which does not impact the current rate; for this reason, it must be interpreted as a “forward guidance shock”. Following Hamilton (as cited in Barakchian & Crowe, 2010) and Barakchian and Crowe (2010), policy rate and forward guidance shocks could be labelled as a “level” and “slope” or “yield” factors respectively, with the former isolating the portion of new information in the FOMC announcement which influences near-term rates only and the latter instead quantifying the effect of new information on further out rates.

Nakamura and Steinsson (2018) make use of the same inputs, but they condense monetary policy surprises into a single dimension by taking only the first principal component of rates’ changes (Bauer & Swanson, 2022) for simplicity, assuming it is sufficient to summarize all the relevant information; the authors refer to them as “policy news shocks”.

Positive policy rate, forward guidance and policy news shocks indicate that the Federal Reserve is more restrictive than expected, i.e., they characterize *contractionary* monetary policies; by contrast, negative shocks identify *expansionary* monetary policies.

The high frequency shock series derived by Romer and Romer (2004) is also placed within the category of traditional measures, even though it is not estimated from futures rates by means of PCA. Rather, as explained in section 2.2 with reference to monthly surprises, Romer and Romer (2004) measure monetary shocks as the component of the change in the federal funds rate that cannot be predicted from the Fed’s staff forecasts (Acosta, 2022).

Rebalancer ownership

A consistent and reliable measure of rebalancer ownership is key in the analysis, considering the stated goal of uncovering the importance of rebalancing demand for the transmission of monetary policy impulses. Rebalancer ownership (*RO*) appears twice in the model, both as a standalone variable – to capture the *unconditional effect* of rebalancing strategies on stock returns – and within an interaction term with monetary shocks (*MS*). The latter variable detects the impact of rebalancing strategies on stock returns *in response to a monetary policy shock*; accordingly, it is viewed as the variable of interest. In more concrete terms, its coefficient (β_1), capturing the potential correlation between rebalancer ownership and monetary surprises, provides a proper quantification of the value of the portfolio rebalancing channel within the transmission mechanism of monetary policy.

Thomson Reuters provides data on institutional investors' ownership for all 114 companies in the two samples, differentiating among multiple entities. For most firms, institutional investors are split into seven categories: closed-end funds, exchange-traded funds, hedge funds, insurance companies, investment trusts, mutual funds, and pension funds. The expression "institutional investor", however, is not a synonym of "rebalancing institution": rather, rebalancers only represent the sub-group of institutional investors that tend to adjust their portfolios to achieve predetermined investment targets; from this, the necessity to filter only for those institutional investors that could be reasonably deemed to be rebalancers. A detailed explanation of the procedure adopted to isolate rebalancers' holdings is available in Appendix B.

Control variables

Countless variables may affect stock returns besides rebalancer ownership. To account for the most relevant ones, model (3.1) also considers a set of control variables along with their interaction with Nakamura and Steinsson (2018) policy news shocks.

While many papers introduce a wide collection of control variables, data availability poses remarkable constraints on the number of controls that could be added as well as on the methodology to retrieve them. Therefore, model (3.1) accounts for three of them only, namely:

- Size (market capitalization) – measured as the natural logarithm of market equity; [23]
- Monetary policy exposure (MPE) index;
- Book-to-market ratio.[24]

Controlling for the company's size and book-to-market ratio is rather standard in the literature, in the wave of the revisions of the Capital Asset Pricing Model (CAPM) proposed by Fama and French (1992). Already during 80s, a vast stream of research indeed challenged the main assumptions of the CAPM, among which

[23] Market equity is computed as the product between the number of shares outstanding during a quarter and the average price during the same quarter. Since Thomson Reuters does not provide average price measures, the latter is found as the mean of each company's closing price on each trading day during a specified quarter.

[24] Despite stocks are classified into a "value" and "growth" category based on their book-to-market ratios, there is still a remarkable within-sample variability which justifies the latter's inclusion as a control variable. Table 3.1 (a) supports this choice by providing a snapshot of the univariate analyses of the book-to-market variable for both samples.

the existence of a single risk factor – the excess return on the market portfolio – shaping firms' expected return. Puzzling empirical results of higher actual risk-adjusted returns compared to CAPM's predictions led to the identification of other factors affecting returns and to the necessity to incorporate them in the original model. Major evidence is provided by Banz (as cited in Fama & French, 1992), who found out that stocks with low market equity tend to outperform large stocks as well as by Rosenberg, Leid and Landstein (as cited in Fama & French, 1992), who noticed a similar behavior between high and low book-to-market stocks.[25] In response, Fama and French (1992) proposed an extended version of the CAPM to account for these two dimensions of risk – namely, firms' relative size and book-to-market ratio. This three-factors model remained pillar in the asset pricing literature for many years, before being further modified to include other risk factors. Considering such evidence, size and book-to-market ratio reasonably enter model (3.1) as control variables; this allows the analysis to be depurated from from the impact they might have on returns, thereby wiping out the possibility of high (low) returns driven by the firm's small (large) size or its high (low) book-to-market ratio.

The monetary policy exposure (MPE) index introduced by Ozdagli and Velikov (2016) allows to control for additional firm characteristics deemed to shape the relationship between monetary policy and stock returns. Specifically, the MPE index considers the firm's liquidity position, the duration and the volatility of its cash flows, its financial constraints – measured through the Whited-Wu (WW) index – and its operating profitability as the five most relevant drivers of an asset's exposure to monetary policy. More details about such variables and their construction are provided in Appendix C.

The firm characteristics mentioned above become predictor variables in a regression with stock daily returns around FOMC dates as the outcome variable:

$$r_{i,t} = \gamma_0 + \gamma_1 X_{i,t} \, x \, MS_t + \gamma_2 X_{i,t} \, x \, MS_t + \delta_t + u_t \qquad (3.6)$$

where $X_{i,t}$ is a $N \, x \, 5$ matrix – with N denoting the number of observations – containing the explanatory variables; δ_t is a set of meeting and industry fixed effects.

This regression is a "preliminary step" to be performed to get the MPE index: the latter is finally set up by combining coefficients associated to interaction terms with sample data for the corresponding independent variables. The final MPE indexes for NYSE and NASDAQ sample are built as in (3.7) and (3.8) respectively:

[25] This is obviously not an exhaustive list of authors and their findings; for example, Bhandari (as cited in Fama and French, 1992) finds a positive relation between leverage and return as well. Challenges to the empirical validity of the CAPM attracted much attention during 80s and 90s; studies on the topic are indeed countless.

$$MPE_{i,t} = 0.00441Cash_{i,t} + 0.0001Dur_{i,t} + 0.0172WW_{i,t} - 0.0317Vol_{i,t} + 0.0775Prof_{i,t} \quad (3.7)$$

$$MPE_{i,t} = 0.084Cash_{i,t} + 0.0109Dur_{i,t} + 0.0186WW_{i,t} - 0.0099Vol_{i,t} + 0.0578Prof_{i,t} \quad (3.8)$$

where $Cash_{i,t}$ = cash and short-term investments, $Dur_{i,t}$= cash flow duration, $WW_{i,t}$ = WW percentile rank, $Vol_{i,t}$ = cash flow volatility and $Prof_{i,t}$ = operating profitability of firm *i* in quarter *t*. [26] Interestingly, all coefficients preserve their sign across the two samples, despite having different values and significance levels. Signs match those derived by Ozdagli and Velikov (2016) and Lu and Wu (2021), except for the equity duration one. Positive duration coefficients are puzzling; in contrast with most evidence, indeed, stocks with higher duration exhibit lower returns in response to a positive monetary policy shock.

3.2 Empirical results

This section presents the results from the main analyses carried out on NYSE and NASDAQ samples; related tables are reported in the text given their relevance. First, each table is analyzed individually; then, a comparison between the results is provided.

3.2.1 Results for NYSE sample

Before precisely quantifying the effect of rebalancing demand on stock prices through model (3.1), a more aggregate analysis is presented to detect the *total* impact of monetary policy on stock returns, thereby abstracting from the role of the portfolio rebalancing channel in the propagation of monetary shocks. Following Lu and Wu (2021) and Ozdagli and Velikov (2016), daily returns are regressed on Nakamura and Steinsson (2018) monetary policy surprises as a stand-alone variable in a model with no fixed effects[27]:

$$r_{i,t} = c_0 + c_1 MS_t + \varepsilon_t \quad (3.9)$$

Results are reported, in decimals [28], in column 1 of Table 3.7 (a). The coefficient c_1 equals -0.00401 (that is, -40.1 bp) and, with a p-value equal to zero, it is significant even at 1%. Both the sign and the significance of such coefficient coincide with

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[26] Differently from model (3.1), *t* here indexes quarters rather than days.

[27] [27] Ozdagli and Velikov (2016) carry out the same regression but employing GSS (2005) shocks. Chapter 3.3.2 presents the results in terms of these alternative shocks.

[28] All results are reported in decimals; most of them are however interpreted in basis points (bp).

estimates from Lu and Wu (2021), notwithstanding the difference in the coefficient itself. [29] Accordingly, at the *aggregate l*evel – without distinguishing between rebalancer and non-rebalancer ownership – a restrictive monetary policy of increasing interest rates has a negative and statistically significant impact on value stock returns.

Jarociński and Karadi (2018) identify the source of a "negative co-movement" between interest rates and stock valuations in a pure "monetary policy shock". News about restrictive monetary policies indeed leads to lower returns for two reasons:

- First, higher interest rates increase the discount rate of future expected payoffs.
- Second, a restrictive monetary policy signals worse future economic conditions, leading to downward revisions in payoffs' expectations themselves.

"Central bank information shocks", that instead isolate the portion of information divulged by the FOMC which does not refer to monetary policy, is responsible for a "positive co-movement" between interest rates and equity performance. Being Nakamura and Steinsson (2018) shocks measures of monetary policy shocks, rather than central bank information shocks, the negative coefficient estimated is in line with the argument of Jarociński and Karadi (2018).

As anticipated, regression (3.9) merely helps to understand the *unconditional* impact of a monetary policy shock on stock returns; however, it does not allow to assess the role of rebalancing demand within the monetary policy transmission mechanism. Other regressions in Table 3.7 (a) tackle this issue by adding, as independent variables, rebalancer ownership and its interaction with monetary policy shocks as per model (3.1). From column 3 to column 5 the model is also gradually expanded by incorporating three control variables along with their interaction with Nakamura and Steinsson (2018) shocks. Meeting and industry fixed effects are included from the second to the fifth regression; industry fixed effects, where industry is identified through the firm's four-digits NAICS code, must be intended as the interaction between the firm industry and monetary shocks.

As anticipated in section 3.1, the attention should be placed on the coefficient associated to interaction term $RO_{i,t}\, x\, MS_t$ (β_1): a beta different from zero signals that the stock revaluation due to a monetary policy shock depends on the level of rebalancer ownership; when negative, as in all regressions from (2) to (5), stocks with a higher percentage of rebalancer ownership are subject to a more remarkable downward price adjustment in response to a positive exogenous monetary policy shock ($MS_t > 0$). Column 5 contains results for the complete model with all control variables: if FOMC opts for a 10 bp increase in interest rates,

[29] Lu and Wu (2021) obtain an estimate of -8.9 bp, still significant at 1%.

stocks with additional 10% rebalancer ownership are subject to 1.4 bp higher fall in returns, on average. The underlying explanation is immediate: since perceived as risky securities, rebalancers tend to shift away from value stocks when policy rates increase. The negative impact of rebalancing demand is, however, never significant, even at the 10% threshold.

Column 6 presents the empirical output of a fully saturated model which also includes Nakamura and Steinsson (2018) shocks without meeting and industry fixed effects. With such modifications to regression (3.1), a positive monetary policy shock still has a negative effect on stock returns, but it becomes statistically insignificant at all relevant thresholds. The variable $RO_{i,t}\, x\, MS_t$ preserves its sign and significance, but with a remarkable fall in p-value compared to previous regressions.

Outcomes of this analyses are only partially in line with the results obtained by Lu and Wu (2021): while they also find out a negative relationship between the interaction term of interest and stock returns, their full model coefficient estimate is equal to -3.7 bp and it is significant even at 5%. Consistently with their outcomes, however, its absolute value increases, its p-value falls and the Adj. R^2 of the regression improves when additional control variables are introduced in the model. This behavior reveals biases in the basic model in column 2 due to omitted variables; under the assumption that the complete model in column 5 is correctly specified, the coefficient of interest could instead be interpreted as the causal effect of the interaction term $RO_{i,t}\, x\, MS_t$ on value stock returns.[30]

3.2.2 Results for NASDAQ sample

The same analysis is now repeated for NASDAQ sample to highlight potential differences with respect to the impact rebalancing demand on growth stocks. Table 3.7 (b) in the next page presents the outcomes.

The first column shows the results of regression (3.9) applied to NASDAQ sample. As it happens for value stocks, an unexpected positive monetary policy shock causes a drop in returns on growth stocks; again, the effect of such shock is statistically significant a 1%. The monetary shock coefficient, however, shows that growth stocks tend to re-evaluate less than value stocks; specifically, they enjoy a 10.4 bp lower fall in return (29.7 bp against the 40.1 bp decrease in returns on value stocks).

From column 2 to 5 monetary shock as a standalone variable is removed, appearing only within interaction terms with other regressors. The negative

[30] Discrepancies in the results should not be surprising since they can be justified by a plenty of differences in model fundamentals. The most relevant refer to different companies in the dataset, time windows, number of control variables and alternative considerations in the computation of rebalancer ownership.

coefficient of the variable of interest ($RO_{i,t}\ x\ MS_t$) suggests that higher rebalancer ownership is associated to a higher fall in the price of growth stocks in response to a monetary policy contraction. The 3.1 bp fall in return is higher than that experienced by value stocks and much closer to the estimate of Lu and Wu (2021), but it is still not significant at all relevant thresholds. Finally, removing time and industry fixed effects as in column 6, the effect of a positive Nakamura and Steinsson (2018) monetary policy shock becomes insignificant even at 10%.

With the sample beginning in January 2000, it is legitimate to be perplex about possible biases that the late 90s "dot.com bubble" may produce on the results for NASDAQ sample, given the prevalence of tech companies it is characterized by. To overcome this issue, the baseline analysis is replicated for two restricted samples from January 2002 to December 2015 and from January 2004 to December 2015, thereby excluding the final years of the crisis. Outcomes are not subject to material changes even after ignoring such periods.

Overall, the similar results obtained for the two samples mutually support the idea of a negative impact of rebalancer ownership on the aggregate stock market in response to monetary shocks. Only minor differences could indeed be highlighted as to the value and the significance of the coefficients of interest and model performance. The slightly higher coefficients (and lower corresponding p-values) in Table 3.7 (b) uncover a more relevant effect of rebalancing demand on growth relative to value stocks. In a plain model with no control variables, a higher 10% rebalancer ownership indeed implies a 2.4 bp fall in NASDAQ returns against the far moderate fall of 0.6 bp in NYSE ones in response to a positive monetary policy shock. With a return difference of 1.8 bp, the fall in value stock return is just one-fourth of that experienced by growth stocks; freed the coefficients of interest up from potential contaminations of the originally omitted control variables, such delta decreases to 1.7 bp in the fully saturated model. This signals a more prominent rebalancing activity around growth stocks; that is, a higher selling (buying) pressure for growth stocks in response to restrictive (expansionary) policies.

As it comes to goodness of fit, the two analyses do not allow to assess which is the best model – whether a fully saturated model or a basic one without controls; the behavior of the Adj. R^2 is indeed quite surprising and hard to interpret. Adding variables increases performance of NASDAQ sample regressions; the peak is indeed reached in the fully saturated model. When employing NYSE sample, the fully saturated model has instead the lowest Adj. R^2; with a value of 0.2972, it is 0.002 lower than the Adj. R^2 of the basic model with no extra regressor.

3.3 Alternative tests

This section presents alternative tests to the portfolio rebalancing main analysis to validate and/or confute the outcomes so far obtained. Specifically, in the first subparagraph the full sample analyses presented in section 3.2 are replicated employing GSS (2005) target and path factors rather than Nakamura and Steinsson (2018); in the second test, while still employing Nakamura and Steinsson (2018) surprises, the sample is restricted to the three years between 2007 and 2009 to examine the role of the portfolio rebalancing channel during the Great Recession.

3.3.1 Alternative measures of shocks: GSS (2005) target and path factors

Nakamura and Steinsson (2018) develop their policy news shock based on GSS (2005) surprise measures. GSS (2005) characterize FOMC's monetary policy news through a "target" and a "path" factor, retrieved by applying PCA to the changes in five Federal Funds and Eurodollar futures rates listed in chapter 3.1.

While GSS (2005) measure clearly decouples a policy rate and a forward guidance effect, Nakamura and Steinsson (2018) single factor condenses them into a unique dimension; the main analyses in chapter 3.2 therefore assess the role of rebalancing demand in response to *joint* conventional (policy rates) and forward guidance shocks. To that end, GSS (2005) distinct shocks' measures allow for a more detailed examination of the contribution of the portfolio rebalancing channel in the transmission of each *individual* policy. While different, GSS (2005) factors and Nakamura

Pairwise correlation coefficients in Table 3.8 above indicate a higher covariation between Nakamura and Steinsson (2018) measure and GSS (2005) path factor, stressing that the former mostly incorporates unexpected news affecting *future* rather than *current* rates. Such values are consistent with GSS (2005), who point out that in recent years forward guidance shocks make up the bulk of unexpected FOMC announcements.

Table 3.9 (a) and (b) show the results. With no fixed effects, positive policy rate and forward guidance shocks both have a negative and statistically significant effect on value and growth stock returns (column 1 in (a) and (b)). Remarkably, however, value stocks revaluate more than growth stocks in response to both policies, with deltas of 28.6 bp and 9.9 bp in case of positive shocks to the target and the path factor respectively. Without controlling for equity duration, the first result is not surprising; value stocks are indeed expected to be affected more by unexpected changes in current interest rates given their short run cash flows. Such explanation is however inconsistent with the second evidence: growth stocks, with higher cash flows later in time, should instead be more sensitive to forward guidance shocks. It is therefore reasonable to suspect that other variables, besides equity duration, are omitted in the single linear regression model in column 1.

By contrast, results for the two fixed effects models (columns 2 and 3 in both panels of Table 3.9) partially deviate from the original outcomes when forward guidance shocks are employed.

In response to a positive policy rate shock, prices of value and growth stocks with a higher percentage of rebalancer ownership fall, consistent with the predictions in chapter 1; just as in the baseline model with Nakamura and Steinsson (2018) composite shock measure, this effect is not significant. Surprisingly, however, the selling pressure from rebalancers is higher for growth rather than for value stocks, given that NASDAQ portfolio revaluates downward by 1.7 bp more than NYSE's one (2.5 bp against 0.8 bp).

In the framework unconventional forward guidance measures, the rebalancing behavior adopted by certain investors triggers opposing effects on stock valuations: higher rebalancer ownership indeed leads to an appreciation of value stocks and a concurrent depreciation of growth stocks. Specifically, value stocks with higher rebalancer ownership experience an increase in return of 1.3 bp while growth stocks revaluate downward by 2.5 bp, at least according to the fully saturated model in the third column.

While none of the two effects is statistically significant, it is still worth to investigate this phenomenon on account of close evidence provided by the literature. A similar pattern is, for example, documented by Avalos and Todorov (2022) in relation to the post-Covid 19 monetary tightening, that induced investors to increase their holdings of value stocks while selling off growth equities between 2021 and 2022. The different timing of cash flows provides the most reasonable explanation for such rebalancing tendency: with prospects of higher *future* interest rates, rebalancers tend to decrease their holdings of growth stocks, since they are characterized by delayed cash flows. This is the essence of an active "interest rate anticipation" strategy that Reilly and Brown (2012) primarily discuss as regards to bonds, but that could be easily applied to stock as well [31]: when interest rates are expected to increase, investors shift to assets with a shorter duration, thereby less sensitive to interest rate changes (less volatile).

Interestingly, Avalos and Todorov (2022) also consider the progressive deleveraging of leveraged exchange-traded funds (leveraged ETFs) as a potential exacerbating factor for the recent shift.[32] These "rebalancing flows across equities"

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[31] According to Reilly and Brown (2012), indeed, interest rate anticipation strategies are "highly scalable since they can be implemented with virtually any securities available in the market".

[32] Leveraged ETFs mainly invest in risky growth stocks, thereby linking their asset under management (AUM) to their prices. There is a negative relationship between AUM and leverage:

(Gnabo & Soudant, 2022) testify that monetary policy does not only activate a portfolio rebalancing mechanism *across* sectors but also *within* asset classes themselves or, at least based on these results, within the equity market.

3.3.1 Portfolio rebalancing during the global financial crisis

Inflation targeting strategies generally pursue price stability as their primary goal.[33] Secondary goals may include achieving full employment and balanced economic growth (ECB), supporting the government's economic policies (Bank of England) and contributing to the stability of the financial system (Bank of England, Bank of Japan, Federal Reserve). Until Lehman's Brothers collapse, conventional policies oriented toward price stability were thought be sufficient to guarantee financial stability and to meet other "subordinated" objectives altogether. The Great Recession broke down such certainties. The crisis, on the one hand, brought to light financial markets' extreme vulnerability; on the other, it revealed the limits of CMP in prompting their recovery, leading the way to a *forced* development of UMP measures. Still, conventional monetary policy remained operative throughout the entire crisis period, even after the introduction of QE and other non-standard interventions: dramatic policy rate cuts indeed occurred starting from mid-2007 and continued for the subsequent years at a sustained pace; as an indicative figure, the federal funds rate fell from 1.81% to 0.16% just between September and December 2008. Overall, combining both conventional and unconventional actions, monetary policy during the Great Recession was marked by an unprecedented expansionism.[34] The financial and economic turbulences, together with the innovations in central bankers' behavior that characterized this period, justify the interest in examining the role of rebalancing during the most crucial years of the crisis.

Table 3.10 (a) and (b) show the main results of model (3.1) applied to a restricted sample of three years from 2007 to 2009 for NYSE and NASDAQ stocks respectively. The third (fully saturated) regressions in the leftmost sections of the two tables show that a in response to a positive monetary policy shock – considering both negative and positive surprises – rebalancing toward safer assets leads to a fall in value and growth stock returns, by 2.5 bp and 1.9 bp respectively. With noticeably high p-values associated to the coefficient of interest, rebalancing

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when the former falls, the latter increases and vice versa. However, with target levels of leverage to respect, when leverage exceeds the predefined target, these funds engage in selling offs of these securities; as in Avalos and Todorov (2022), this causes a "rotation" from growth to value stocks.

[33] United States, from this perspective, is an exception. The Federal Reserve is indeed entrusted with a "dual mandate" consisting in pursuing maximum employment and price stability altogether.

[34] Such expansionistic tendency is also evident from the sign of shocks: out of the 24 shocks occurring from January 2007 to December 2009, 15 are negative monetary policy shocks.

demand is not significant at explaining such negative performances, as already pointed out by the main analysis. Differently from the latter, however, value stocks tended to reevaluate a bit more than growth stocks during the Great Recession.

The portfolio rebalancing device worked as expected in response to expansionary shocks, leading to higher value and growth stock returns in response to expansionary shocks during the crisis. Curiously, instead, it had a contrasting impact on stock prices following positive surprises: while driving poorer performance of value stocks (-13.7 bp), higher rebalancer ownership also leads NASDAQ stocks to appreciate and increase in returns (+ 11.2 bp). Even if none of the two effects is significant, growth stocks' response is rather surprising, given the ex-ante expectations about a negative relationship between monetary policy and rebalancing demand discussed in chapter 1. Gnabo and Soudant (2022) find similar evidence considering stock reaction to ECB's conventional policies between the end of 2002 and 2016. Splitting their sample into "value", "core" and "growth" stocks, they observe that increases in the main refinancing operations rate (MRO) leads to rebalancing flows *away from value stocks* and *toward growth stocks*. As in the European case, restrictive monetary policies during the crisis therefore incentivize rebalancing agents to privilege growth investing strategies, substituting value stocks within their portfolios. The result obtained can be reconciled with such evidence considering that Nakamura and Steinsson (2018) series, during the crisis, appears to be mostly made of shocks to policy rates rather than shocks to forward guidance, at least by inspecting correlations with GSS (2005) shocks in Table 3.12.

As anticipated in section 3.1, Nakamura and Steinsson (2018) propose a composite shock measure which accounts for policy rate as well as for forward guidance shocks; Table 3.9 shows that their shock has a higher correlation with GSS (2005) path factor rather than target factor supporting the idea that, over the full sample, forward guidance shocks are predominant in FOMC announcements. Puzzlingly, however, Table 3.11 shows that this result is reversed during the years of the crisis. [35]

Such "rebalancing flow across equities" (Gnabo & Soudant, 2022) is also supportive of a "failure of value investing" as documented by Lev and Srivastava (2020). According to Lev and Srivastava (2020), it seems that value investing started losing its appeal from 2007 onward, inverting a long-lasting tendency of overperformance compared to growth-oriented strategies. Possible concurrent causes of such phenomenon trace back to accounting imprecisions and errors in

[35] Such evidence is surprising considering that during the crisis central banks intensified their usage of forward guidance.

certain measures, such as the book value of equity, relevant for classification of stocks [36] as well as to a mean reversion process between value and growth stocks.

Minor changes from previous analyses relate to the regression coefficients in bold in Table 3.10 (a) and (b). First, in the single linear regression of stock returns on restrictive surprises only, the monetary shock coefficient is positive and significant (at 10% and 5% in NYSE and NASDAQ regressions respectively). Second, rebalancing demand has a positive significant effect on growth stock valuations during a monetary tightening, at least as predicted by the basic model (Table 3.10 (b), section 3, column 2); considering both positive and negative monetary shocks, it also has a negative significant effect on value stock returns (Table 3.10 (a), section 1, column 2). Despite the dissimilarity with other results, such effects are negligible, since they only occur in a plain model with no control variables, whose performance (as measured by the Adj. R^2) is lower than that of a fully saturated model.

Table 3.12 recaps stock market implications of portfolio rebalancing in response to the various policies examined in both chapter 3.2 and 3.3, thereby allowing to grasp immediately and in more concrete terms the results discussed above.

[36] According to Lev and Srivastata (2020), book values of equity are often understated as costs associated to self-developed items – such as intangibles, R&D, brand value or brand name – are expensed rather than being capitalized. Since they are not recorded on the balance sheet, they do not show up in the book value of equity’s measurement.

Conclusion

This paper contributes to the asset pricing literature by providing further empirical evidence on the relationship between monetary policy, stock prices and portfolio rebalancing. With respect to the *bilateral* relationship between monetary policy and equity performance, the former is here proven not to strongly affect the stock market, in sharp contrast with the outstanding literature. In numerical terms, while different depending on the measure of shock employed, its effect is indeed always insignificant.

Narrowing the attention on *how* monetary policy decisions propagate to the stock market, most papers stress the centrality of the portfolio rebalancing channel. From this standpoint, the results here presented also describe a slightly different reality. Indeed, while matching the empirical prediction of a negative impact of rebalancing demand on stock returns in response to monetary policy shocks, none of the analyses shows evidence of a significant relationship between them, with just an exception. This clearly downsizes the relevance of the portfolio rebalancing channel in the transmission of monetary policy impulses.

Interestingly, this paper deepens the discussion about the mechanism of portfolio rebalancing by differentiating its effect on value and growth stocks. Baseline results support the idea of a similar functioning of the portfolio rebalancing channel for value and growth stocks, with the latter appearing a bit more sensitive to unexpected changes in monetary policy. In general, however, outcomes obtained for the two samples offer mutual support in favor of the insignificance of portfolio rebalancing is in explaining stock returns.

Alternative tests in chapter 3.3 also prove the poor relevance of the portfolio rebalancing channel for stock market developments. All analyses are indeed coherent with baseline results, showing that, while it seems some rebalancing tendency exist, its relevance is rather negligible. At the same time, these alternative tests open to potential rebalancing flows across equities (Gnabo & Soudant, 2022) in response to certain kinds of monetary policy actions. As explained in section 3.3.1, rebalancing institutions tend to disinvest in growth stocks while increasing their holdings of value stocks in response to positive forward guidance surprises. Higher future interest rates indeed incentivize rebalancers to substitute value stocks with growth stocks, driving returns down for the former and up for the latter. In addition, rebalancing flows also emerge when only restrictive policies enforced during the crisis are considered (chapter 3.3.1) but with reversed direction. Negative surprises do not lead to such effect; rather, rebalancers increase their demand for all types of equities during expansionary times, in line with ex-ante expectations. In both cases, the most likely explanation for such phenomenon traces back to the timing of cash flows generated by value and growth stocks. Importantly, however, upward and downward revaluations due to rebalancing demand are never significant, leading to the conclusion that while some kind of rebalancing flow may exist, it is not relevant to explain the resulting changes in valuations.

In conclusion, the contribution of this paper is manifold. First, it provides support to previous studies in relation to the negative relationship between monetary policy and stock returns as well as between rebalancing demand and equity performance. Second, however, it downsizes the role of monetary policy and of the portfolio rebalancing channel, so much emphasized in related research. Finally, it explores the effectiveness of portfolio rebalancing within different segments of the equity market, showing that stocks with different underlying features may have contrasting reactions to the same policy change. The latter topic appears to be particularly relevant and with potential to be further expanded: indeed, while countless evidence has been provided on the role of the portfolio rebalancing channel for the aggregate stock market performance as well as on different asset classes, the scarcity of studies aimed at differentiating its importance *within* the equity sector is still remarkable.

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Appendixes

A Principal Component Analysis

Richardson (2009) defines principal component analysis (PCA) as a sophisticated technique based on mathematical principles which allow to "reduce the dimensionality of large datasets"; indeed, large datasets create non-negligible scalability issues, making the analysis of individual variables and their relationships more cumbersome. PCA represents a valid and reliable tool to overcome such problem; by linearly combining original variables into a smaller set of new variables (Bro & Smilde, 2014), it allows to extract all relevant information and derive meaningful data summaries.

Following Bro and Smilde (2014), suppose X is a $N\,x\,K$ matrix of independent variables (the dataset at hand), where N denotes the number of observations and K the number of variables. With large N and/or K, resorting to PCA could be worthwhile to substantially simplify the analysis.

PCA linearly combines variables in X into a unique variable t as:

$$t = Xw \qquad \text{(A.1)}$$

where $w = [w_1, \ldots w_K\ ]$ is a vector of originally randomly chosen weights. From a geometrical perspective, t is the least squares line of best fit (Richardson, 2009) passing through the data, i.e., the line that minimizes the sum of squared residuals. Specifically, the t-line is found as the solution of the following minimization problem (Bro & Smilde, 2014):

$$\begin{gathered} \min_{w}(t - wX)(t - wX)' \\ \text{subject to } ww' = J \end{gathered} \qquad \text{(A.2)}$$

where J is a $N\,x\,1$ vector with unit length. Minimizing the sum of squared residuals as in (A.2) is equivalent to maximizing the variance of t under the same constraint:

$$\begin{gathered} \max_{w} t't = w'X'Xw \\ \text{subject to } ww' = J \end{gathered} \qquad \text{(A.3)}$$

where $t't = w'X'Xw$ is the variance of t.

Otherwise stated, t is the variable that "reduces the dimensionality of the dataset while preserving the maximum variability, i.e., statistical information, of the original variables" (Jolliffe & Cadima, 2016). This alternative version of the problem in (A.3) provides the intuition behind the unit norm constraint imposed on the optimal weights in (A.2) and (A.3): if weights were allowed to have arbitrary large values, no limit would be imposed on the variance of t as well (Bro & Smilde, 2014). In a more formal terminology, the t-line is called "first summary index" (PC1), since it is the first approximation of the original data; projections of original observations on the t-line are referred to as "scores".

In most models, PC1 is not sufficient to explain all the relevant information offered by the dataset: usually, a second summary index (PC2) – found as the line orthogonal to PC1 – is derived to further approximate data.

B Rebalancer ownership

Fender (2003) classifies institutional asset managers, i.e., institutional investors, into collective investment investments institutions (CIIs) – such as hedge funds, mutual funds or investment funds – insurance companies and pension funds. The latter two are not regarded as collective investment vehicles but rather as part of insurance and pension subsector (OECD, 2008). Most of these institutional investors do not fall within the definition of "rebalancing institution". After data about *all* institutional investors' holdings are collected, it is therefore necessary to filter only for those that, among them qualify as "rebalancers"; the methodology adopted is briefly described below.

First, institutional ownership data for each company are accessed on each day of interest.[37] "Ownership data" refers to the following three items:

- *Fund holdings*: (adjusted) percentage of traded shares held by each institutional investor;
- *Fund type:* category of institutional investor owning that percentage;[38]
- *Fund name*: complete name of the institutional investor (ex: Vanguard Equity Index Portfolio).

Raw data are then subject to a screening procedure aimed at isolating the sample of rebalancers. In a first step, funds that do not meet a set of pre-established criteria are excluded *(first exclusion step)*. Such criteria pertain to the fund type and/or the fund name as follows:

[37] With respect to rebalancer ownership, the "day of interest" is usually day *before* the FOMC announcement; if data are not available on this day, the day immediately before is taken.

[38] As explained in chapter 3.1, Thomson Reuters distinguishes seven categories of institutional investors: closed-end fund, exchange-traded fund, hedge fund, insurance company portfolio, investment trust portfolio, mutual fund, pension fund portfolio.

- *Fund type*: among the seven categories of institutional investors Thomson Reuters provides data for, only mutual funds, insurance company portfolios and pension fund portfolios are selected as *potential* rebalancers. This approach slightly differs from that adopted by Lu and Wu (2021) in multiple aspects. First, they do not list insurance funds among the rebalancers' category; however, since OECD (2008) explicitly classifies insurance companies and pension funds as belonging to the same subsector ("insurance and pension subsector"), they can be somehow assimilated to pension funds, considered rebalancers by construction. Second, since they employ ownership data coming from two distinct sources, they carry out two analyses – focusing on pension and sovereign wealth funds and mutual funds separately. Since Thomson Reuters provides comprehensive ownership data on seven fund types, the three rebalancing categories selected are here considered altogether. Finally, sovereign wealth funds are excluded, being Thomson Reuters silent on them.
- *Fund name*: funds whose name contains references to the equity sector are excluded, since they can be for sure identified as pure equity funds. Following Bodie, Kane and Marcus (2012), these are funds that invest 95% or more of their portfolios in equities, with the remaining percentage (4% or 5%) consisting of short-term securities or cash held to deal with eventual share redemptions by investors.[39]

The second step aims at keeping those funds that meet extra criteria to qualify as rebalancers *(inclusion step)*. Specifically, only the following categories of funds are selected:

(1) All pension funds are kept, since rebalancing attitudes are commonly observed in pension funds beyond balanced funds and sovereign wealth funds (Lu & Wu, 2021);
(2) Insurance and mutual funds whose name include one or more of the following words or expressions: "balance", "retirement", "target", "income", "moderate", "aggressive", "conservative", and "total return";
(3) Insurance and mutual funds that are known a-priori to be rebalancers, despite they do not contain any of the words listed in (2)

[39] Specifically, funds are eliminated from the sample if their name includes "eq" or "stock"; the latter is used in place of complete words such as "equity" or "equities", since many pure equity funds just contain "eq" in their name. A material and legitimate concern might relate to the erroneous elimination of funds with "eq" in their name where "eq" is a portion of words other than "equity" or "equities", such as "equally" or "equally weighted". This issue rarely materializes and in most instances funds with equally weighted portfolios are pure equity funds as well; as an example, Invesco V.I: Equally Weighted S&P 500 Fund is a pure equity fund investing only in S&P 500's stocks.

The choice of words in (2) is motivated by Vanguard suggested investments asset allocations (Reilly & Brown, 2012): depending on the investment objective – whether the fund seeks income generation, growth, or balance – Vanguard suggests an indicative percentage of the portfolio to be invested in cash and short-term assets, bonds, or stocks. If the percentage invested in equity exceeds 95%, the fund is considered a pure-equity fund, as per Bodie, Kane and Marcus (2012), and excluded from the rebalancers' sample. Table B.1 offers a simplified version of the Vanguard suggested asset allocations' schema provided by Reilly and Brown (2012), with a short guideline on its interpretation.

Words listed in (2) are key to assess whether a fund's investment strategy is oriented toward rebalancing. On the contrary, fund names containing "growth" or "capital" are not typical of rebalancing institutions. Funds having "capital" in their name, indeed, generally seek capital appreciation, development, growth, or accumulation. To pursue this goal, they mainly invest in equities; hence, they are consistently identified as pure-equity funds. An exception is represented by two funds – namely, "Polo Capital SICAV SA" and "Amaurota Capital SICAV SA" – which contain the word "capital" in their name but invest less than 95% of their portfolio in equities.

The approach so far implemented sharply reduces the amount of data to be analyzed; however, the sample may still be contaminated by non-rebalancers. The third step provides further adjustments, again excluding some funds based on the investment strategy suggested by their name *(second exclusion step)*. Words to be excluded are grouped in 3 categories:

- *Asset allocation*: funds characterized by "flexible" and "tactical" asset allocations tend to adjust the composition of their portfolios to reflect short-term changes and take advantage of changing market conditions (Reilly & Brown, 2012), without a predefined target equity mandate; funds whose name contains references to this kind of asset allocation are therefore excluded from the sample;
- *Growth and income funds*: these kinds of funds usually have a "mixed" strategy – they both purse capital growth and current income; however, since most of them invest only in equity instruments, a more consistent approach categorizes them as pure equity funds.[40]
- *Aggressive strategies*: the adjective "aggressive" was selected before as many funds with an aggressive strategy should be considered rebalancers; these are "moderately aggressive funds" or funds pursuing an "aggressive income" strategy, according to Vanguard suggested investments asset allocations (Reilly & Brown, 2012). However, those with an "aggressive growth" strategy are pure-equity funds: consequently, if the fund has a

[40] In most instances, indeed, capital growth is the primary objective while current income the secondary one. See for example Integrity Growth & Income Fund's investment strategy.

name containing expressions such as "aggressive growth", "aggressive opportunities" or "aggressive investors", it is excluded.

Importantly, rebalancer ownership data refer to the percentage of traded shares held by rebalancers the *day before* the FOMC announcement day. To this extent, despite the time index t of the variable $RO_{i,t}$, the rebalancers' percentage holdings value is computed at $t-1$.[41]

C Monetary Policy Exposure (MPE) index

This appendix expands the discussion about the variables included in the monetary policy exposure (MPE) index based on Ozdagli and Velikov (2016).

Cash and short-term investments

Considering cash within the MPE index aims at capturing the potential "liquidity effects" (Ozdagli & Velikov, 2016) of a monetary policy shock. Depending on how firms choose to hold their cash, positive or negative liquidity effects might occur: if firms keep their cash in an interest bearing account, positive monetary policy shocks will benefit them through an increase of their savings; on the contrary, it will be detrimental for firms holding cash outside a deposit, due to the increased opportunity cost of holding money (Ozdagli & Velikov, 2016). Considering that companies might hold cash in both forms, the sign of the coefficient associated with the cash variable in the MPE index regression should be interpreted as an indication of which effect is *predominant*. Following Ozdagli and Velikov (2016) and Lu and Wu (2021), the variable "Cash" equals the firm's cash and short-term investments scaled by its market capitalization.

Whited -Wu (WW) index

The Whited – Wu (WW) index (Whited & Wu, 2006) provides a reliable measure of a firm's financial constraints, i.e., it tells how costly is to raise new equity compared to use internal financing, as a function of various observable firm characteristics. Here only four firm-specific characteristics, namely cash flows, dividends, total assets and sales growth, are considered.

Different measures of cash flows have been proposed in the literature. Lu and Wu (2021) compute cash flows as the difference between net income and depreciation and amortization; Hou, Xue & Zhang (2021) sum net income before extraordinary items and depreciation; other authors, focusing on the company's operations, instead use net cash flows from operating activities as a measure of

[41] If rebalancer ownership data are not available for $t-1$, then percentages from the first available date are taken (usually, data of the previous two or three days can be found; in just one case, previous week data have been used).

cash flows. Here the approach proposed by Hou, Xue & Zhang (2021) is followed; however, the second addendum is substituted with a more comprehensive measure of depreciation, depletion, and amortization, due to the lack of data about depreciation only. This measure of cash-flows is different from the one to build the other two cash flows-based variables – namely cash-flow duration and cash-flow volatility.

In line with the procedure adopted by most papers, dividends are introduced through an indicator variable, which takes value 1 if the firm pays dividends and 0 otherwise. Precisely, a check on whether the company pays dividends is performed by looking at quarterly data on dividends per share and preferred shares: if they are both zero, it is then reasonable to believe the firm pays no dividends; in such case, the indicator variable is assigned a value of zero.

Whited and Wu (2006) also add industry sales growth and total long-term debt to the index; although their inclusion could have really improved the estimation, they are here excluded because of the too many missing values in the long-term debt series and difficulties in retrieving industry-related data. Following Ozdagli and Velikov (2016) and Lu and Wu (2021), percentile ranks are used in place of the exact WW index value.

Cash flow (equity) duration

Including a measure of cash flow (equity) duration is meant to account for the riskiness of the company's cash flows. Equivalent to the more familiar concept of bond duration, cash flow duration expresses the weighted-average life of the cash flows, with weights being equal to the period in which the cash flow occurs; as such, it is a measure of the interest rate sensitivity of a company's cash flows.
Two key issues are however encountered when deriving equity rather than bond duration (Dechow, Sloan & Soliman, 2004):

(1) *Infinite cash flows:* differently from bonds, equity does not have a specified maturity; hence, while the number of coupon payments is finite, the stream of dividends generated by equity could be potentially infinite;[42]
(2) *Cash flows' forecasts:* forecasting challenges arise because, contrarily to coupon payments, dividends are unknown (there is no certainty that they will be paid and, whether they are, what is the precise outflow).

Dechow, Sloan and Soliman (2004) tackle problem (1) by partitioning cash flows into a "finite" and an "infinite" component: setting a forecasting time horizon T, cash flows generated from $t = 1$ to $t = \mathrm{T}$ are *finite* cash flows while those occurring

[42] The only exception is represented by "perpetual bonds" - bonds without maturity and with fixed coupon payments for an infinite time horizon (Osservatorio sui Conti Pubblici Italiani, 2020). These bonds, however, only exist "in theory" as there is no example of a bond with such features currently in circulation.

from t = T + 1 to $t = \infty$ are *infinite* cash flows. Infinite (terminal) cash flows are expressed as a level perpetuity:

$$\sum_{t = T + 1}^{\infty} \frac{CF_t}{(1+r)^t} = (MC - \sum_{t = 1}^{T} \frac{CF_t}{(1+r)^t}) \qquad \text{(C.1)}$$

with CF_t being the dividend payout in period t, MC the firm's market capitalization and r the time-invariant discount rate.

Such cash flows' partition leads to a measure of implied equity duration equal to the weighted average of the duration of the finite cash flows and the infinite cash flows:

$$D = (w_f * Dur_f) + (w_i * Dur_i) \qquad \text{(C.2)}$$

where Dur_f and Dur_i denote the duration of the finite and the infinite component of cash flows, respectively, and w_f and w_i denote the weights associated to each of them.

In accordance with Dechow, Sloan and Soliman (2004), the duration of infinite cash flows is found as:

$$Dur_i = \mathrm{T} + \frac{(1+r)}{r} \qquad \text{(C.3)}$$

The estimation of the other three inputs – Dur_f, w_f and w_i – is a more laborious procedure, as it draws upon forecasts of future cash flows. As explained in point (2), this is a demanding task: differently from cash flows measures employed to construct the WW (2006) financial constraints' index and cash flow volatility, here *projected* rather than *historical* cash flows should be used. Dechow, Sloan and Soliman (2004) resort to the approach developed by Nissim and Penman (*2001*) to forecast cash flows to be used to estimate duration, based on projected earnings and book value of equity. The forecasting horizon is set at 10 years; given that data are provided on a quarterly basis, the forecasting period in the analysis thus equals 40 quarters (T = 40).
Cash flows in future period t (CF_t) is found as:

$$CF_t = E_t - (BV_t - BV_{t-1}) = BV_{t-1} \left[\frac{E_t}{BV_{t-1}} - \frac{(BV_t - BV_{t-1})}{BV_{t-1}}\right] \qquad \text{(C.4)}$$

where:

- E_t denotes company's earnings in period (quarter) t;
- BV_t denotes company's book value of equity in period t;
- BV_{t-1} denotes company's book value of equity in period $t-1$.

Based on formula (A.3.4), cash flow estimation implicitly requires earnings and book value of equity to be forecasted first.
Book value of equity in period *t* is computed as:

$$BV_t = BV_{t-1} \, x \, g^{BV}_{t-1} \qquad \text{(C.5)}$$

where g^{BV}_{t-1} is the sales growth rate the period before. Despite the term g^{BV}_{t-1} could be reasonably expected to denote the growth rate in the book value of equity, rather than the sales growth rate, Nissim and Penman (2001) evidence shows that the latter is a better predictor of future equity growth rather than the growth rate of the book value of equity itself. To that end, Dechow, Sloan and Soliman (2004) rely on sales growth rate for the estimation of future book values of equity.

Earnings in period *t*, still dependent on the book value of equity in period $t-1$, are estimated as:

$$E_t = BV_{t-1} \, x \, ROE_t \qquad \text{(C.6)}$$

where ROE_t denotes return on equity in period *t*.

In ultimate instance, cash flow estimation hinges upon forecasting the sales' growth rate (g^{BV}) and ROE. On the grounds of the evidence provided by Nissim and Penman (2001), that document a mean reverting behavior in both sales growth rate and ROE, the two variables are forecasted through a first order autoregression: the autocorrelation coefficients are set equal to 0.57 and 0.24 respectively. [43]

Once cash flows are forecasted for the entire time horizon, both their *present value* and their *time-weighted present value* is computed. Present value is simply found as the ratio between the expected cash flow at time *t* and the discount factor of the same period; time-weighted present value is then the product between such present value and the period in which the cash flow itself occurs. The discount rate (cost of equity) is set equal to 0.12 as in Dechow, Sloan and Soliman (2004).

[43] These autocorrelation coefficients are set based on the value to which the two variables are assumed to revert toward after the forecasting horizon of 10 years. Specifically, ROE is assumed to revert to a mean value equal to the cost of equity while sales growth rate to the long-run GDP growth rate. Dechow, Sloan and Soliman (2004) assume a long-run cost of equity equal to 0.12 and a long-run GDP growth rate of 0.06; while it is plausible that such values and the resulting autocorrelation coefficients might differ across companies, authors apply the same coefficients to forecast cash flows of two totally unrelated companies – namely, Amazon and Alaska Air Corporation; hence, despite having distinct samples and firms, the forecasting parameters are chosen to be equal for all of them.

Market capitalization *(MC),* the present value of cash flows – *PV(CF)* – and the time-weighted present value of cash flows – *TW PV (CF)* – can be finally combined to build the duration measure in (C.2).

Finite cash flows duration is derived as:

$$Dur_f = \frac{TWPV(CF)}{PV(CF)} \qquad \text{(C.7)}$$

The weight associated to the finite cash flow component instead depends on market capitalization:

$$w_f = \frac{PV(CF)}{MC} \qquad \text{(C.8)}$$

Finally, under the constraint that the two weights must sum up to 1, $w_i = 1 - w_f$. The approach described above establishes a clear link between equity duration and the timing of a firm's cash flows (Avalos & Todorov, 2022). Value stocks are expected to react less to discount rate changes thanks to their earlier and steadier cash flows, being therefore characterized by a shorter duration. Due to their higher proportion of cash flows in the distant future, growth stocks are instead more sensitive to changes in interest rates. Table 3.1 (c) supports this argument.

Cash flow volatility

Several different approaches to estimate cash flow volatility can be found in the literature. Minton and Schrand (1999) compute it as the coefficient of variation of operating cash flows – namely, the standard deviation of operating cash flows normalized by the absolute value of the mean; Allayannis, Rountree and Weston (2005) as well as Lu and Wu (2021) instead focus on the standard deviation of the last 20 quarters of operating cash flows scaled by total assets. Choosing the second estimation technique, cash flow volatility of each company is found by first normalizing net cash flows from operating activities by total assets and then computing, for each quarter, the standard deviation over the previous 20 quarters. Thomson Reuters' data about net cash flows are available for most years; missing values that can be found are mostly concentrated in the period from 2000 to 2005. To obtain more accurate standard deviation measures – particularly for the initial period – these "gaps" are filled with the help of the weighted moving average (WMA) technique. WMA allows to exploit current and past data to forecast future values of key financial figures; the procedure draws upon the choice of specific weights to be assigned to the inputs – generally, a higher weight is placed on more recent data – to predict upcoming values by means of a weighted average. Despite being generally implemented in forecasting analysis, WMA's logic is flexible enough to handle the issue of incomplete samples as well.

Missing observations are indeed estimated through WMA with a forecasting window of five quarters (T = 5). Differently from a standard WMA, subsequent rather than previous data are employed, in view of the considerable number of missing values at the beginning of the sample and the impossibility to forecast them based on past figures. Identifying the right weights for each period represents a not negligible issue. This problem is solved through a four-steps procedure (*t* denotes the quarter in which a missing value occurs):

(1) *WMA (1)*: WMA is first applied to the missing value's nearest figure available (at $t + 1$), by assigning random weights to the latter's closest data (data from $t + 2$ to $t + 6$, given the five quarters horizon);

(2) *Error and mean squared error (MSE):* forecasts in (1) are compared with the actual value of net cash flows at $t + 1$, obtaining the related forecasting error and mean-squared error (MSE);[44]

(3) *Optimal weights*: optimal weights are then found as the weights that lead to the lowest MSE, i.e., the weights that yield the most accurate forecasts in terms of MSE;

(4) *WMA (2)*: optimal weights in (3) are applied to actual net cash flows from $t + 1$ to $t + 5$ to retrieve the missing value at time *t*.

A far easier technique is instead employed to replace missing values in the sample of total assets: thanks to the extremely low number of missing data, gaps are legitimately with the simple average of available data for each specific company in the sample.

Operating profitability

Operating profitability is computed as the ratio between the firm's operating profit and the market value of its assets. The latter is given by the net between total assets and shareholders' equity plus market capitalization. Ozdagli and Velikov (2016) work out the profit measure as the difference between sales and the cost of goods sold only, without allowing for other operating expenses to be subtracted; their measure of operating profitability is therefore the ratio between the firm's gross profits and the market value of its assets. In view of accounting for operating expenses other than direct production costs, operating rather than gross profits is here employed following Hou, Xue and Zhang (2021). In computing the ratio between operating profitability and book value of equity (OPE), the former is indeed found as revenues minus the sum of cost of goods sold, selling, general and administrative expenses (SG&A) and interest expenses.

[44] The error and the mean-squared error both measure the precision of the forecast, quantifying the distance between actual and the projected values. The error is given by the difference between actual and the projected net cash flows (at $t + 1$); the mean squared error is instead the ratio between the sum of squared errors and the number of forecasting periods.

Tables and figures

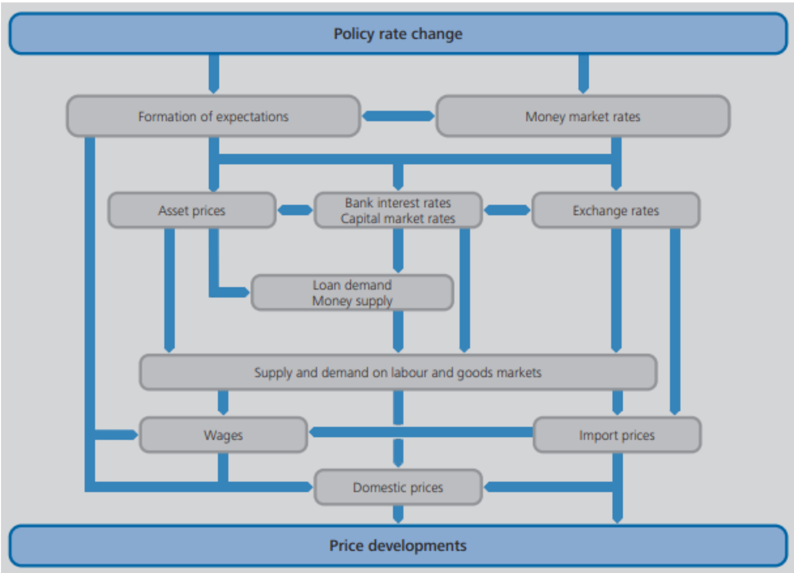

Figure 1.1: The transmission mechanism of conventional monetary policy (CMP) in "interest rate-based monetary policy regimes" (Khatat, Loercks & Fleuriet, 2020). Source: Deutsche Bundesbank (2017).

Monetary Shocks	Gertler-Karadi	Short sample Romer-Romer	Long sample Romer-Romer
Gertler-Karadi	1	0.2440	0.2634
Short sample Romer-Romer	0.2440	1	0.9205
Long sample Romer-Romer	0.2634	0.9205	1

Table 2.1: Correlation matrix among Gertler and Karadi (2015) and Romer and Romer (2004) monetary shocks.

Variable	Gertler-Karadi	Short sample Romer-Romer	Long sample Romer-Romer
Intercept	0.1065	-0.0027	-0.0026
Monetary shock (Z)	0.0465	0.1767 ***	0.1692 ***
	(0.131)	*(0.000)*	*(0.005)*
F-stat	11.87	81.02	72.87
Observations	270	336	336

Table 2.2: Results of the first stage regression.

Each column shows the results of the first-stage regression estimated through a different monetary shocks' series as the external instrument: model (1) is estimated using Gertler and Karadi (2015) shocks; regression (2) and (3) are estimated using short sample and long sample Romer and Romer (2004) shocks respectively. The residual of the regression of interest is taken as the outcome variable. Coefficients are reported in percentage points (pp) as in Kekre and Lenel (2022); p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. F-statistics are also reported for each first stage regression.

Variable	Gertler-Karadi	Short sample Romer-Romer	Long sample Romer-Romer
Intercept	0.1157	0.1224	0.1192
Predicted Treasury yield residuals	-8.0392	-0.5329	-1.7826
	(0.145)	*(0.677)*	*(0.182)*
F-stat	2.1382	0.1734	1.7883
Observations	270	336	336

Table 2.3: Results of the second stage regression for excess stock return.

The table shows results for the second-stage regression of reduced form residuals of the excess stock return regression on fitted values from first-stage regression (Treasury yield residuals). Coefficients are reported in percentage points (pp) as in Kekre and Lenel

(2022); p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. F-statistics are also reported for each second stage regression.

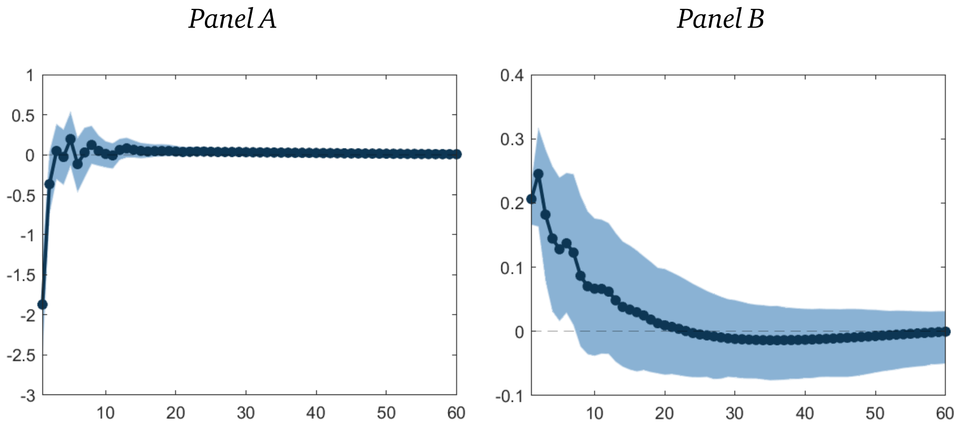

Figure 2.1.1: Impulse response functions of one-year Treasury yield (panel A) and excess equity return (panel B) to a Gertler and Karadi (2015) monetary policy shock.

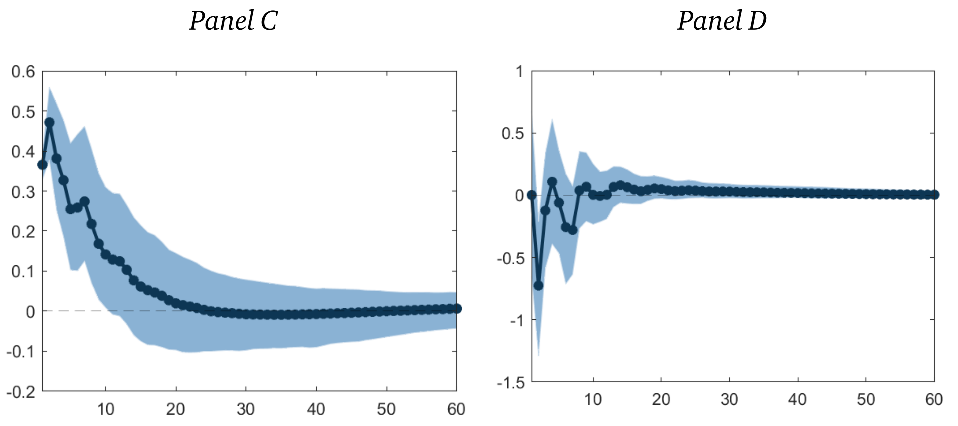

Figure 2.1.2: Impulse response functions of one-year Treasury yield (panel C) and excess equity return (panel D) to a short sample Romer and Romer (2004) monetary policy shock.

Panel E *Panel F*

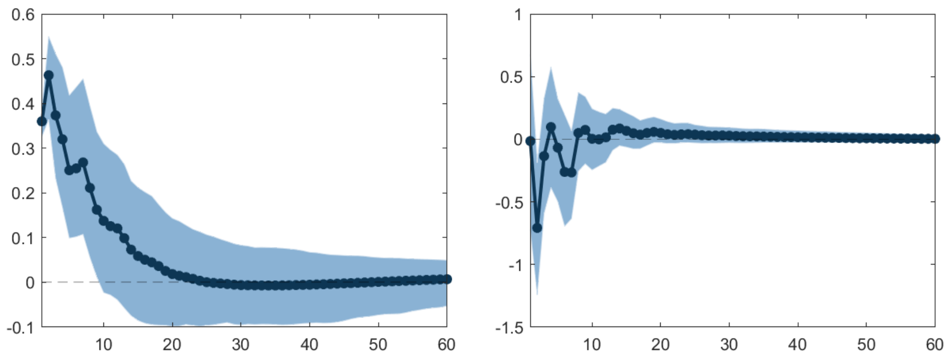

Figure 2.1.3: Impulse response functions of one-year Treasury yield (panel E) and excess equity return (panel F) to a long sample Romer and Romer (2004) monetary policy shock.

Book-to-market	Obs	Mean	SD	Min	Median	Max
NYSE	7296	**1.77**	19.95	-46.51	0.54	746.34
NASDAQ	7222	**0.36**	0.47	-16.90	0.28	9.46

Table 3.1 (a): Univariate descriptive statistics of the book-to-market ratio variable for both samples.

The table reports univariate analyses for NYSE and NASDAQ samples' book-to-market ratios. Book-to-market ratio is computed as the ratio between a firm's book value of equity and its market capitalization. Book value of equity is found as the difference between total assets and total liabilities; market capitalization is the product between number of shares and price. A negative book-to-market ratio originates from a negative book value of equity.

NYSE stocks exhibit a much higher book-to-market ratio, being thereby classified as value stocks. Moreover, the figures provide evidence of the within sample variability (standard deviation) in terms of book-to-market ratio, especially in NYSE sample. This justifies its inclusion as a control variable in model (3.1).

Market cap	Obs	Mean	SD	Min	Median	Max
NYSE	7246	**21.66**	1.95	14.35	21.50	31.84
NASDAQ	7226	**23.12**	1.54	16..82	23.11	40.36

Table 3.1 (b): Univariate descriptive statistics of the log (market cap) variable for both samples.

The table reports univariate analyses for NYSE and NASDAQ samples' log (market cap), where market capitalization is found as the product between number of shares and price. In line with the expectations, NYSE stocks exhibit a lower market capitalization compared to NASDAQ stocks, even though with a slightly larger variability.

Equity duration	Obs	Mean	SD	Min	Median	Max
NYSE	7165	**22.86**	35..04	-100	11.42	100
NASDAQ	7062	**23.22**	31.04	-100	11.90	100

Table 3.1 (c): Univariate descriptive statistics of the equity duration variable for both samples.

The table reports univariate analyses for NYSE and NASDAQ samples' cash flow (equity) duration. Equity duration is computed following Dechow, Sloan and Soliman (2004), using a time horizon of 40 quarters and a discount rate equal to 0.12. Differently from bond duration, there is no upper or lower bound for equity duration; to avoid biases caused by potential outliers, the maximum and the minimum values for yearly duration are therefore set equal to 100 years and -100 years. More details can be found in Appendix C.

Over the fifteen years sample considered, NYSE stocks exhibit lower duration compared to NASDAQ stocks, in line with its classification as a sample of value stocks

Year	Annual BM Ratio NYSE	Annual BM Ratio NASDAQ
2000	3.153094893	0.298396828
2001	3.531524157	0.325229155
2002	3.037508922	0.411987247
2003	7.531433254	0.439355813
2004	2.798714226	0.357113836
2005	1.667500116	0.342554491
2006	0.828735631	0.322201736
2007	0.532554836	0.305925079
2008	0.668839903	0.383428498
2009	0.768081206	0.473874835
2010	0.694531133	0.411075057
2011	0.674061149	0.381726371
2012	0.648487923	0.379537714
2013	0.552759997	0.332125885
2014	0.526826139	0.284578978
2015	0.527841561	0.253958159

Table 3.2: Average annual book-to-market values of NYSE and NASDAQ samples respectively.

Book-to-market ratio is computed as the ratio between a firm's book value of equity and its market capitalization. Book value of equity is found as the difference between total assets and total liabilities; market capitalization is the product between number of shares and price. All inputs are available for each company at quarterly frequency (quarterly price is the *average* price for the quarter). The procedure to compute annual average measures is as follows: quarterly book- to-market values for each company are computed first and then averaged to get the *portfolio*'s quarterly book-to-market ratio; the portfolio's annual book-to-market ratio is finally found as the average of the quarterly values.

The table clarifies the higher book-to-market ratio of NYSE compared to NASDAQ stocks, justifying their classification as value and growth stocks respectively.

Year	Equity duration NYSE	Equity duration NASDAQ
2000	23.83606202	27.5543386
2001	22.93676364	23.70466926
2002	25.29977224	27.98919985
2003	25.67396105	27.14683301
2004	24.71579987	27.57825078
2005	24.71579987	23.77042483
2006	24.72520719	21.94291605
2007	24.1718896	22.77100592
2008	21.27329309	19.70696747
2009	24.03314517	26.38448912
2010	23.60103668	24.28094787
2011	23.07396956	20.65343277
2012	17.99943653	19.57663081
2013	19.89779124	20.21332129
2014	20.79144705	19.92081673
2015	19.46542387	19.05240827

Table 3.3: Average cash flow (equity) duration of NYSE and NASDAQ samples respectively, in years.

Cash flow (equity) duration is computed as in Dechow, Sloan and Soliman (2004). A detailed explanation of their procedure can be found in Appendix C. The procedure to compute annual average measures is as follows: equity durations for each compay – originally expressed in quarters – are found following Dechow, Sloan and Soliman (2004) and then averaged to get the *portfolio*'s equity duration; in a second step, the portfolio's equity duration – still expressed in quarters – is found as the average of the such values; finally, equity duration values are divided by 4 to get the corresponding measure in years.

The table shows that for most years in the sample NYSE stocks have a higher cash flow duration compared to NASDAQ stocks, justifying their classification as value and growth stocks respectively.

NAICS Industry group	**Number**
Accounting, Tax Preparation, Bookkeeping, and Payroll Services	2
Aerospace Product and Parts Manufacturing	1
Automotive Parts, Accessories, and Tire Retailers	1
Beverage Manufacturing	2
Clothing and Clothing Accessories Retailers	1
Communications Equipment Manufacturing	3
Computer and Peripheral Equipment Manufacturing	1
Computer Systems Design and Related Services	2
Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services	1
Department Stores	1
Drycleaning and Laundry Services	1
Electric Power Generation, Transmission and Distribution	3
General Freight Trucking	1
Hardware, and Plumbing and Heating Equipment and Supplies Merchant Wholesalers	1
Health and Personal Care Retailers	1
Industrial Machinery Manufacturing	3
Motor Vehicle Manufacturing	1
Other Miscellaneous Retailers	2

Other Professional, Scientific, and Technical Services	1
Pharmaceutical and Medicine Manufacturing	3
Radio and Television Broadcasting Stations	1
Rail Transportation	1
Restaurants and Other Eating Places	1
Scientific Research and Development Services	2
Semiconductor and Other Electronic Component Manufacturing	6
Software Publishers	8
Support Activities for Mining	1
Traveler Accommodation	1
Warehouse Clubs, Supercenters, and Other General Merchandise Retailers	1
Web Search Portals, Libraries, Archives, and Other Information Services	2
Wired and Wireless Telecommunications (except Satellite)	1

Table 3.4 (a): Industry group classification of firms in NYSE Sample.

NAICS Industry group	**Number**
Aerospace Product and Parts Manufacturing	2
Agencies, Brokerages, and Other Insurance Related Activities	1
Clothing and Clothing Accessories Retailers	1
Computer Systems Design and Related Services	2
Converted Paper Product Manufacturing	2
Couriers and Express Delivery Services	1
Cut and Sew Apparel Manufacturing	1
Depository Credit Intermediation	3
Drugs and Druggists' Sundries Merchant Wholesalers	1
Drycleaning and Laundry Services	1
Electric Power Generation, Transmission and Distribution	1
Electrical Equipment Manufacturing	1
General Medical and Surgical Hospitals	1
Grain and Oilseed Milling	1
Hardware Manufacturing	1

Health and Personal Care Retailers	1
Industrial Machinery Manufacturing	1
Insurance Carriers	5
Iron and Steel Mills and Ferroalloy Manufacturing	1
Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	2
Lessors of Real Estate	2
Medical Equipment and Supplies Manufacturing	1
Metal Ore Mining	2
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	1
Nonresidential Building Construction	1
Oil and Gas Extraction	2
Other Electrical Equipment and Component Manufacturing	1
Other Fabricated Metal Product Manufacturing	1
Other General Purpose Machinery Manufacturing	1
Other Nonmetallic Mineral Product Manufacturing	1
Other Transportation Equipment Manufacturing	2
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	1
Petroleum and Petroleum Products Merchant Wholesalers	1
Plastics Product Manufacturing	1
Pulp, Paper, and Paperboard Mills	1
Railroad Rolling Stock Manufacturing	1
Residential Building Construction	2
Restaurants and Other Eating Places	1
Sugar and Confectionery Product Manufacturing	1
Tobacco Manufacturing	1
Utility System Construction	1
Wired and Wireless Telecommunications (except Satellite)	1

Table 3.4 (b): Industry group classification of firms in NASDAQ Sample.

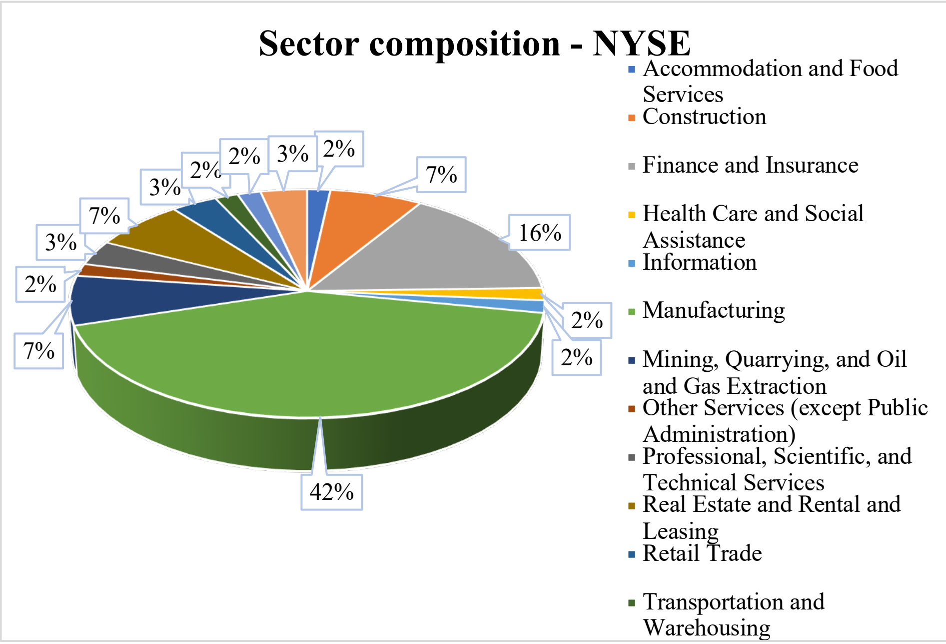

Figure 3.5 (a): Sector composition of firms in NYSE sample.

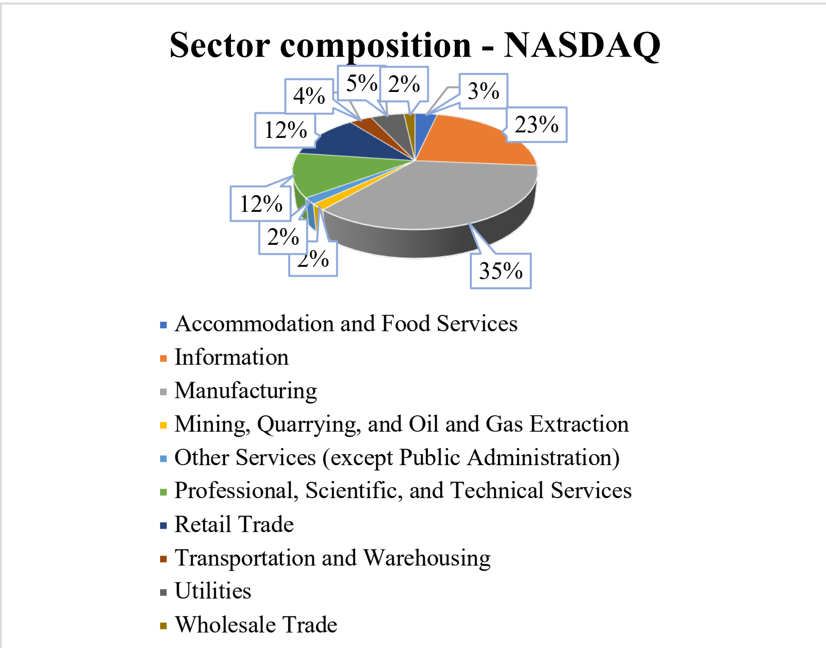

Figure 3.5 (b): Sector composition of firms in NASDAQ sample.

	Coefficient	St. error	t-stat	p-value
Intercept	0.00356 ***	0.0012	3.08	0.004
Cash	-0.00072	0.0015	-0.48	Variable 0.637
Dur	-0.00002	0.0000	-1.65	0.106
WW	-0.00002	0.0000	-0.86ì7	0.392
Vol	0.00388	0.0204	0.19	0.850
Prof	0.0478 ***	0.0078	6.09	0.000
Cash x MS	0.00441 *	0.0026	1.68	0.100
Dur x MS	0.00005 **	0.0000	2.41	0.020
WW x MS	0.01725	0.0000	0.32	0.753
Vol x MS	-0.03174	0.0221	-1.43	0.160
Prof x MS	0.07747 ***	0.0147	5.25	0.000
Meeting FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry FE x MS	Yes	Yes	Yes	Yes

Table 3.6 (a): MPE Index regression for NYSE sample.

Standard errors are clustered at the industry level; p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit. Both industry fixed effects and their interaction with Nakamura and Steinsson (2018) shocks. Stand-alone variables are winsorized at the 1^{st} and the 99^{th} percentile. Variables of interest used to build the MPE Index are highlighted in bold.

Variable	Coefficient	St. error	t-stat	p-value
Intercept	0.00257 ***	0.0008	3.27	0.003
Cash	-0.00413	0.0050	-0.82	0.418
Dur	0.00001	0.0000	0.94	0.354
WW	0.00007 ***	0.0000	3.94	0.000
Vol	-0.01397	0.0095	-1.46	0.154
Prof	-0.05799 *	0.0309	-1.87	0.071
Cash x MS	-0.00840	0.0033	0.00	0.999
Dur x MS	0.01086	0.0206	0.53	0.601
WW x MS	0.01857	0.0000	0.69	0.496
Vol x MS	-0.00987	0.0072	-1.37	0.182
Prof x MS	0.05779 **	0.0265	2.18	0.037
Meeting FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry FE x MS	Yes	Yes	Yes	Yes

Table 3.6 (b): MPE Index regression for NASDAQ sample.

Standard errors are clustered at the industry level; p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1 Coefficients are reported in decimals and rounded to the fifth digit. Both industry fixed effects and their interaction with Nakamura and Steinsson (2018) shocks. Stand-alone variables are winsorized at the 1st and the 99th percentile. Variables of interests used to build the MPE Index are highlighted in bold.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
MS	-0.00401 ***					-0.00449
	(0.000)					*(0.392)*
RO x MS		-0.00006	0.00011	-0.00014	- 0.00014	-0.00023
		(0.839)	*(0.630)*	*(0.520)*	*(0.527)*	*(0.190)*
RO		-0.00029	- 0.00046	-0.00055*	-0.00057*	0.00018
		(0.390)	*(0.140)*	*(0.072)*	*(0.067)*	*(0.465)*
MPE x MS			-	-	-	-
MPE			-	-	-	-
Market cap x MS				-	-	-
Market cap					-	-
BM					-	-
BM x MS					-	-
Meeting FE	No	Yes	Yes	Yes	Yes	No
Industry FE	No	Yes	Yes	Yes	Yes	No
Observations	7,295	3,4 52	3,406	3,406	3,406	7,245
Adj. R^2	0.0232	0.2997	0.2974	0.2977	0.2972	0.0230

Table 3.7 (a): Results of model (3.1) applied to NYSE sample.

The model is progressively saturated by adding control variables to counteract the potential biases caused by omitted variables. Standard errors are clustered at the industry level; p-values are reported in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
MS	-0.00401 ***					-0.00449
	(0.000)					*(0.392)*
RO x MS		-0.00006	0.00011	-0.00014	- 0.00014	-0.00023
		(0.839)	*(0.630)*	*(0.520)*	*(0.527)*	*(0.190)*
RO		-0.00029	- 0.00046	-0.00055*	-0.00057*	0.00018
		(0.390)	*(0.140)*	*(0.072)*	*(0.067)*	*(0.465)*
MPE x MS			-	-	-	-
MPE			-	-	-	-
Market cap x MS				-	-	-
Market cap					-	-
BM					-	-
BM x MS					-	-
Meeting FE	No	Yes	Yes	Yes	Yes	No
Industry FE	No	Yes	Yes	Yes	Yes	No
Observations	7,295	3,4 52	3,406	3,406	3,406	7,245
Adj. R^2	0.0232	0.2997	0.2974	0.2977	0.2972	0.0230

Table 3.7 (a): Results of model (3.1) applied to NYSE sample.

The model is progressively saturated by adding control variables to counteract the potential biases caused by omitted variables. Standard errors are clustered at the industry level; p-values are reported in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit.

Monetary Shocks	NS	GSS target	GSS path
NS	1	0.6263	0.7767
GSS target	0.6263	1	-0.0036
GSS path	0.7767	-0.0036	1

Table 3 . 8 : Correlation matrix among Nakamura and Steinsson (2018) policy news shocks and GSS (2005) target and path factors over the full sample.

	GSS target factor	**GSS path factor**
Variable	(1) (2) (3)	(1) (2) (3)
MS	-0.00312 ***	-0.00257 ***
	(0.000)	*(0.000)*
RO x MS	-0.0001 -0.0008	0.00001 0.00013
	(0.714) *(0.770)*	*(0.965)* *(0.720)*
RO	-	-
MPE x MS	-	-
MPE	-	-
Market cap x MS	-	-

Market cap		-			-	
BM x MS		-			-	
BM		-			-	
Meeting FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Observations	7,295	3,452	3,406	7,295	3,452	3,406
Adj. R^2	0.0156	0.2997	0.2963	0.0088	0.2997	0.2977

Table 3.9 (a): Results of model (3.1) applied to NYSE sample using GSS (2005) target and path factors.

Regression (1) is the unconditional regression of stock returns on monetary shocks, without meeting and industry fixed effects; regression (2) and (3) are fixed effects regressions (respectively the plain and the fully saturated model). Standard errors are clustered at the industry level; p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit. Industry fixed effects should be intended as the interaction between the firm industry and monetary shocks (target and path factors, respectively).

	GSS target factor			**GSS path factor**		
Variable	(1)	(2)	(3)	(1)	(2)	(3)

MS		-0.00026 ***			-0.00158 ***	
		(0.000)			*(0.000)*	
RO x MS		-0.00018	-0.00025		-0.00025	-0.00025
		(0.721)	*(0.563)*		*(0.565)*	*(0.418)*
RO		-			-	
MPE x MS		-			-	
MPE		-			-	
Market cap x MS		-			-	
Market cap		-			-	
BM x MS		-			-	
BM		-			-	
Meeting FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Observations	7,296	4,940	4,890	7,296	4,940	4,890
Adj. R^2	0.0112	0.3398	0.3480	0.0034	0.3398	0.3483

Table 3.9 (b): Results of model (3.1) applied to NASDAQ sample using GSS (2005) target and path factors.

Regression (1) is the unconditional regression of stock returns on monetary shocks, without meeting and industry fixed effects; regression (2) and (3) are fixed effects regressions (respectively the plain and the fully saturated model). Standard errors are clustered at the industry level; p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit. Industry fixed effects should be intended as the interaction between the firm industry and monetary shocks (target and path factors, respectively).

	Policy news shock			**Negative policy news shock (expansionary)**			**Positive policy news shock (restrictive)**		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
MS		-0.00390 ***			-0.00774 ***			**0.00393** *	
		(0.000)			*(0.000)*			*(0.093)*	
RO x MS		**-0.00043** **	-0.00025		-0.00060	-0.00012		-0.00154	-0.00137
		(0.026)	*(0.294)*		*(0.276)*	*(0.847)*		*(0.377)*	*(0.424)*
RO		-			-			-	
MPE x MS		-			-			-	
MPE		-			-			-	
Market cap x MS		-			-			-	
Market cap		-			-			-	
BM x MS		-			-			-	
BM		-			-			-	
Meeting FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	1,367	624	624	854	390	390	513	234	234
Adj. R^2	0.0189	0.1855	0.2141	0.0440	0.1326	0.1969	0.0016	0.4440	0.4424

Table 3.10 (a): Results of model 3.1 applied to the NYSE 2007-2009 dataset.

Regression (1) **is the unconditional regression of stock returns on monetary shocks, without meeting and industry fixed effects**; regression (2) and (3) are fixed effects regressions (respectively the plain and the fully saturated model). Standard errors are clustered at the industry level; p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit. Industry fixed effects should be **intended as the interaction between the firm industry and monetary shocks** (**target and path factors, respectively**). Coefficient estimates obtained when only negative **monetary policy shocks are employed shall be interpreted as in Table** 3.8 (a) and (b).

	Policy news shock			**Negative policy news shock (expansionary)**			**Positive policy news shock (restrictive)**		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
MS		-0.00301 ***			-0.00615 ***			**0.00513** **	
		(0.000)			*(0.000)*			*(0.018)*	
RO x MS		-0.00011	-0.00019		-0.00042	-0.00003		**0.00198***	0.00112
		(0.859)	*(0.706)*		*(0.654)*	*(0.703)*		*(0.058)*	*(0.210)*
RO		-			-			-	
MPE x MS		-			-			-	
MPE		-			-			-	
Market cap x MS		-			-			-	
Market cap		-			-			-	
BM x MS		-			-			-	
BM		-			-			-	
Meeting FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	1,368	912	900	855	570	563	513	342	337
Adj. R^2	0.0233	0.4669	0.4896	0.0625	0.4972	0.5089	0.0077	0.3920	0.4449

Table 3.10 (b): Results of model 3.1 applied to the NASDAQ 2007-2009 dataset.

Regression (1) is the unconditional regression of stock returns on monetary shocks, without meeting and industry fixed effects; regression (2) and (3) are fixed **effects regressions (respectively the plain and the fully saturated model)**. Standard errors are clustered at the industry level; p-values are in parentheses and symbols *, ** and *** indicate significance at 10%, 5% and 1%. Coefficients are reported in decimals and rounded to the fifth digit. Industry fixed effects should be intended as the interaction **between the firm industry and monetary shocks (target and path factors, respectively). Coefficient estimates obtained when only negative monetary policy** shocks are employed shall be interpreted as in Table 3.8 (a) and (b).

Monetary Shocks	NS	GSS target	GSS path
NS	1	0.3667	0.2819
GSS target	0.3667	1	-0.7860
GSS path	0.2819	-0.7860	1

Table 3.11: Correlation matrix among Nakamura and Steinsson (2018) policy news shocks and GSS (2005) target and path factors over the restricted sample (2007-2009).

Analysis	**Monetary shock**	**NYSE Returns**	**NASDAQ Returns**
Main analysis	Baseline (full sample)	1.4 bp	3.1 bp
Alternative test (1.a)	Target factor	0.8 bp	2.5 bp
Alternative test (1.b)	Path factor	1.3 bp	2.5 bp
Alternative test (2.a)	Baseline (2007-2009)	2.5 bp	1.0 bp
Alternative test (2.b)	Expansionary (2007-2009)	1.3 bp	0.3 bp
Alternative test (2.c)	Restrictive (2007-2009)	13.7 bp	11.2 bp

Table 3.12: Summary of the stock market implications of portfolio rebalancing in response to policies examined.

The table provides a summary of the main empirical results presented in chapter 3.2 and 3.3. Specifically, it recaps the effect of rebalancing demand on value and growth stock returns in response to various kinds of monetary policy shocks, as derived from a complete model with all control variables.

A "baseline" shock shall be here intended as a positive monetary policy shock when both positive and negative Nakamura and Steinsson (2018) shocks are considered; "expansionary" shocks are negative shocks only; "restrictive" shocks are only positive shocks. "Target" and "path" factors refer to GSS (2005) policy rate and forward guidance shocks. None of the effects reported is significant in statistical terms, reflecting that rebalancing demand is not that relevant in explaining stock returns.

	Risk profile	Stocks	Bonds
Income	Conservative	0 %	100%
	Moderate	20%	80%
	Aggressive	30%	70%
Balanced	Conservative	40%	60%
	Moderate	50%	50%
	Aggressive	60%	40%
Growth	Conservative	70%	30 %
	Moderate	80%	20%
	Aggressive	100%	0%

Table B.1: Vanguard suggested asset allocations. Simplified version from Reilly and Brown (2012).

The first column of the table distinguishes three kinds of investment strategies: income-oriented, balanced and growth-oriented strategies. Column 2 further classifies them according to three possible risk profiles – namely conservative, moderate and aggressive - resulting in nine alternative investment schemes. Columns 3 and 4 show the suggested portfolio composition for each strategy, considering stocks and bonds as the only asset classes available.

Since geared toward income generation, income-oriented strategies primarily focus on safe assets: even in their most aggressive version, the bulk of their portfolios is invested in bonds. Contrarily, growth-oriented strategies driven by capital appreciation's objectives mostly invest in equities. The stock fraction progressively increases with risk tolerance; growth-oriented funds with an aggressive risk profile may invest even 100% of their portfolios in stocks. Balanced strategies are a mixture of the two, with similar portfolios' fractions invested in equities and bonds; again, the specific portfolio's weights depend on their risk profile.