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Keywords

new Keynesian model, mixed-frequency macroeconomics, behavioural macroeconomics

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Monetary Policy, Stock Prices and Temporal Aggregation in a New Keynesian Model with Behavioural Expectations

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Abstract

In this paper, we investigate the implications of *temporal aggregation*, i.e. the discrepancy between the Data Generation Process (DGP) and the Data Collection Process (DCP), for the design of monetary policy in a New Keynesian macroeconomic framework with boundedly rational agents. We extend the model by Airaudo, Nisticó and Zanna (2015) who investigate if monetary policy should explicitly respond to stock prices due to the presence of a structural linkage between the stock market and the real activity. We stress this rationale in a similar model with agents with heterogeneous boundedly rational expectations by showing that responding to the stock price is further justified when real data is only available at a delay due to temporal aggregation. Under these conditions, reacting moderately to high frequency stock price movements can stabilise both the financial and the real sectors.

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1 Introduction

While in the great majority of macroeconomic models the frequencies of the Data Generation Process (DGP) and the Data Collection Process (DCP) are implicitly or explicitly assumed to be the same, "[t]here is simply no reason to believe that the frequency at which economic time series are collected coincides with the frequency at which economic agents make decisions" (Christiano and Eichenbaum, 1987, p.64). In the case of macroeconomic aggregates such as the economy's GDP, in particular, data is collected and reported much less frequently than it is generated, due to the substantial costs of such processes. This situation, in which a variable's evolution through time cannot be observed at all dates in which it is generated, is known as *temporal aggregation* and has been widely investigated – mostly from the time series analysis perspective –, by e.g. Theil (1954), Mundlak (1961), Sims (1971), Zellner and Montmarquette (1971), Stock (1987), Marcet (1991), Marcellino (1999), and more recently, by Chan (2022).

In spite of the potential usefulness of averaging or summarizing high frequency data into lower frequencies e.g. in eliminating high-frequency noise that may obscure more relevant behaviour, theory predicts that temporal aggregation leads to non-trivial losses of information about the underlying data processes, especially with regards to their true statistical properties (Rossana and Seater, 1995). Further, temporal aggregation and the choice of sampling frequency are especially relevant when assessing the persistence of macroeconomic aggregates (Paya, Duarte and Holden, 2007), modelling the dynamics of asset price volatility (Perron and Shi, 2020), studying spill-over effects of financial uncertainty shocks on the real economy (Ferrara and Guérin, 2018), or assessing the adequateness of monetary policy rules (Bayar, 2014).

While temporal aggregation is particularly relevant for macroeconomic data, financial market data is, by contrast, readily available at frequencies that are almost as high as that of their DGP. As a result, the information set available to the public and policy-makers consists of data of different frequencies: financial market data is available, in general, at high frequencies, and macroeconomic data at lower frequencies. While this issue is widely acknowledged (see e.g. Christensen, Posch and van der Wel, 2016), there is no clear consensus on how macroeconomic and financial data should be linked consistently in a theoretical model, instead of simply assuming a uniform frequency for all macroeconomic and financial variables, as it is usually done in the great majority of the macroeconomic models (see e.g. Woodford, 2003).

Against this background, the main objective of the present paper is to analyse to what extent the macroeconomic and financial stability of an economy would be affected by a monetary

policy rule that reacts to daily (available) stock prices, instead of using only their quarterly averages (to match the frequency of macroeconomic variables), and so losing intra-quarter information. We analyse this issue from a behavioural macroeconomics perspective, starting with the premise that agents, due to cognitive or informational constraints, use simple expectational rules-of-thumb to forecast macroeconomic and financial variables instead of using model-consistent or "rational" expectations in the sense of Muth (1961). Accordingly, the availability of data will significantly influence the updating frequency of their expectations, which will in turn have non-trivial effects on the dynamics of the economy. It should be emphasised that our objective is not to argue for a monetary policy rate that would react on a daily basis in response to stock price fluctuations, but to quantify the informational "losses" from temporal aggregation from a theoretical perspective, and to indirectly highlight the importance of econometric mixed-frequency techniques as discussed in Carriero, Clark and Marcellino (2015) for real-time nowcasting and policy-making.

The role of asset prices in monetary policy design has been widely investigated in the literature, also from a behavioural perspective, see e.g. Kontonikas and Ioannidis (2005), Kontonikas and Montagnoli (2006), Bask (2011), Westerhoff (2012), Naimzada and Pireddu (2014), Caines and Winkler (2018), and more recently, Kotb and Proaño (2023). However, the debate upon whether monetary policy should respond to asset prices/bubbles is anything but settled. Economists who argue against this proposal, stress that asset prices are too volatile, too unrelated to the real economy, and/or with misalignments that are difficult to detect. Furthermore, a wrong response (e.g. over responding) may lead to excess output volatility (see, e.g. Gertler, Issing and Goodfriend, 1998 and Cogley, 1999). Bernanke and Gertler (1999, 2001) state that price stability and financial stability are complementary; by stabilising prices and output, the monetary authority may also stabilise asset prices. In other words: responding to inflation and output captures the benefit of asset price targeting, without risking the costs (i.e. excess volatility, the baggage of the appearance of interfering in the workings of financial markets, etc.). On the other hand, Gilchrist and Leahy (2002), for instance, assert that all these concerns would appear to argue for caution in using asset price information, rather than ignoring such information. They, as well as e.g. Gilchrist and Saito (2008) and Dong, Miao and Wang (2020), explain that, whether targeting asset prices (or asset bubbles) is beneficial, depends on the information structure of the economy, the particular interest rate rule adopted by the central bank and/or the type of shocks hitting the economy – an argument that is also supported by our analysis.

Relevantly, Chen and Phelan (2021) suggest that financial-sector considerations alone justify at least an additional rate cut during a financial crisis beyond what would be implied by

a standard Taylor rule responding to output gaps. More specifically, policies that combine leaning against the wind in good times, with accommodative rates during financial distress, can substantially improve stability. Further, the consequences of monetary policy for financial stability are state-dependent: the stability benefits of monetary policy depend critically on the timing, with the greatest potential benefits coming when rate cuts occur during financial crises. Following another approach, Caballero and Simsek (2022) design a model where monetary policy operates through financial markets: the central bank affects asset prices, which in turn affects aggregate demand with a delay.

We investigate our research question by incorporating temporal aggregation of real macroeconomic variables in the New Keynesian model developed by Airaudo et al. (2015). While assuming that the economy's overall DGP is of a daily frequency, and that agents use simple expectational rules-of-thumb based on observed data we show that the effect of temporal aggregation in the real sector can be reduced through an interest policy rule that reacts to the daily available stock market prices. In our mixed-frequency dynamic framework, the daily available financial data can serve as a proxy for the real data, which is assumed to be available on a quarterly basis only. Moderately targeting this "proxy" can simultaneously stabilise the financial sector as well as the real sector, on which data is available with a significant delay. We thus provide a further argument for monetary policy to take asset prices fluctuations into account.

We stress in this paper the *cost of waiting*, i.e. waiting for the official collection and publication of the real data as opposed to reacting to the second best indicator for the performance of the (real) economy: the stock price. One can argue for the relevance of this rationale for the policy design during the Covid-19 pandemic. The *statistical darkness* (Tissot and de Beer, 2020) brought by the harsh and sudden disruption of economic activities on the one hand, and the urgent need for timely and solid policy response on the other hand, strongly highlighted the call for high-speed (even real time) statistics and supplementary data. Tissot and de Beer (2020) describe how the traditional macro statistics, which are usually available on an annually, a quarterly, or at best a monthly basis were not sufficient for the policy makers, as the rapid dynamics of the crisis called for information on going developments on more frequently, (i.e. on a weekly or even daily basis). In a crisis time, Tissot and de Beer (2020) explain, there exists the need to go beyond the standard offering of official statistics and reach for more timely, frequent and well-documented indicators to guide policy. This would offer the benefit of mixing different types of data (e.g. daily financial prices, weekly indicators, monthly industrial output and quarterly GDP) (see also Irving-Fisher-Committee, 2021 and Basurto, Dawid, Harting, Hepp and Kohlweyer, 2023).

The remainder of this paper is organised as follows. In section 2 we present our mixed-frequency behavioral macroeconomic model, and describe in detail the assumed Data Collection Process. In section 3 we conduct some dynamic adjustments and discuss the results of our numerical exercises. In section 4, we investigate the rationale of targeting asset prices by the monetary authorities. In section 5 we draw some final conclusions from this study.

2 Theoretical Framework

2.1 The Original Model by Airaudo et al. (2015)

The starting point for our analysis is the theoretical New Keynesian model developed by Airaudo et al. (2015), see also Nisticò (2012). Just as the great majority of macroeconomic models specified in discrete time, this model has a quarterly frequency (Airaudo et al., 2015, p. 1287). In our representation of the model, and to distinguish between the quarterly frequency adopted in this model and the mixed frequency that will be assumed in the rest of the paper, we denote by q the quarterly time index, and use the subscript t to denote daily frequency. Further, let T^q denote the number of "trading days", i.e. days with economic activity, in a quarter. Following Lengnick and Wohltmann (2013, 2016), we assume for simplicity that there is no economic activity (stock market trading, goods production, etc.) on the weekends, so that $T^q = 64 \approx 3 \cdot 30 \cdot \frac{5}{7}$ days per quarter. This implies that a quarter (q) is defined to contain the days $64(q-1)+1, \ldots, 64q$.

In a nutshell, the model developed by Airaudo et al. (2015) is a New Keynesian DSGE model with financial markets and an indefinite number of cohorts of non-Ricardian agents who survive between any two subsequent periods with constant probability $1-\gamma$, where γ is the turnover ratio. A non-zero turnover ratio in financial markets between long-time traders (holding assets) and newcomers (entering the market with no assets) makes financial markets intertemporally incomplete, and hence partially hinders the agents' traditional consumption smoothing schedule. As a result, the wedge between the current and the expected level of aggregate consumption is driven not only by the ex ante real interest rate, as in the standard New Keynesian model, but also by the market value of financial wealth, since the latter is responsible for the difference between the consumption level of long-time traders and newcomers. Airaudo et al. (2015) call the mechanism through which stock price fluctuations feedback into real activity via their wealth effects on consumption the *Finanical Wealth channel* (FWC).

Using the quarterly time index q, the log-linearised version of the Airaudo et al. (2015) model is described below. The demand-side block, the supply-side block, the financial-side

block and the forward-looking Taylor rule are respectively presented by (see Airaudo et al., 2015 eqs. 20-26):

$$
\begin{aligned}
y_q &= \frac{1}{1+\psi} E_q y_{q+1} + \frac{\psi}{1+\psi} s_q - \frac{1}{1+\psi}(r_q - E_q \pi_{q+1}), && (1)\\
\pi_q &= \tilde{\beta} E_q \pi_{q+1} + \kappa(1+\chi)(y_q - z_q), && (2)\\
s_q &= \tilde{\beta} E_q s_{q+1} - \lambda E_q y_{q+1} - (r_q - E_q \pi_{q+1}) + \varphi z_q, && (3)\\
r_q &= \phi_\pi E_q \pi_{q+1} + \phi_s E_q s_{q+1}, && (4)
\end{aligned}
$$

where y_q represents the aggregate demand, π_q the price inflation rate, r_q the policy nominal interest rate and s_q the stock price in a quarter q, all represented as percentage deviations of the original variables from their respective steady-state values, that is, $x_q = \log(X_q/X)$. $z_q = \rho_z \cdot z_{q-1} + \nu_q$ is an AR(1) technology shock, where $\rho_z \in (0,1)$ and ν_q is an i.i.d. disturbance. The FWC (i.e. effect of stock price fluctuations on the real activity) is captured by the term $(\frac{\psi}{1+\psi})$. $\tilde{\beta} \equiv \frac{\beta}{1+\psi}$ is the discount factor β adjusted for a positive turnover ratio γ. The composite coefficient ψ is equal to:

$$\psi \equiv \gamma \frac{1-\beta(1-\gamma)}{(1-\gamma)\epsilon} \frac{1+r}{r},$$

where ϵ is the elasticity of substitution across differentiated goods and r is the steady state real interest rate. The latter is equal to (see Airaudo et al., 2015, p.1300):

$$
\begin{aligned}
r &= f(\beta, \gamma, \epsilon)\\
&= \frac{(1-\gamma)(1-\beta) + \frac{\gamma[1-\beta(1-\gamma)]}{\epsilon} + \sqrt{\Psi}}{2\beta(1-\gamma)}, \text{ where} && (5)\\
\Psi &\equiv \left[(1-\gamma)(1-\beta) + \frac{\gamma[1-\beta(1-\gamma)]}{\epsilon}\right]^2 + 4\,\frac{\gamma[1-\beta(1-\gamma)]\beta(1-\gamma)}{\epsilon} > 0.
\end{aligned}
$$

Finally,

$$
\begin{aligned}
&\kappa \equiv \frac{(1-\theta)\left(1-\theta\tilde{\beta}\right)}{\theta},\\
&\lambda \equiv (1-\tilde{\beta})[(\epsilon-1)(1+\chi)-1] \quad \text{and} \quad \varphi \equiv (1-\tilde{\beta})(\epsilon-1)(1+\chi)\rho_z,
\end{aligned}
$$

where θ is the Calvo price stickiness probability, and $\chi \equiv \frac{N}{1-N}$ is the inverse of the (steady-state) Frisch elasticity of labour supply N.

The relevance of the turnover rate γ in the model is easily outlined: A nonzero value for γ establishes the feedback between the stock market and the real economy. As the turnover rate goes to zero, only infinitely lived traders operate in the market, $\psi \to 0$, $\tilde{\beta} \to \beta$, the FWC vanishes (i.e. $\frac{\psi}{1+\psi} \to 0$) and the model collapses to the benchmark New Keynesian model where there is no rationale for monetary policy to target stock prices (see e.g. Bernanke and Gertler, 2001, Bullard and Schaling, 2002 and Carlstrom and Fuerst, 2007).

2.2 A Mixed-Frequency Representation of the Model

In the following, we explain the mechanism through which we alter the representation of the model's frequency to incorporate and analyse the issue of temporal aggregation. More specifically, we adopt a mixed frequency framework in which financial and policy data is generated and collected daily, while real data is generated daily, but collected only quarterly. As will be made clear below, a mixed frequency framework is capable of capturing such a delay in collecting data relative to its generation process.

The log linearised mixed-frequency version of the model is described by:

$$y_t = \frac{1}{1+\psi}\tilde{E}_q y_{q+1} + \frac{\psi}{1+\psi}s_t - \frac{1}{1+\psi}(r_t - \tilde{E}_q\pi_{q+1}), \tag{6}$$

$$\pi_t = \tilde{\beta}\tilde{E}_q\pi_{q+1} + \kappa(1+\chi)(y_t - z_t), \tag{7}$$

$$s_t = \tilde{\beta}^d\tilde{E}_t s_{t+1} - \lambda\tilde{E}_q y_{q+1} - (r_t - \tilde{E}_q\pi_{q+1}) + \varphi z_t, \tag{8}$$

$$r_t = \phi_\pi\tilde{E}_q\pi_{q+1} + \phi_s\tilde{E}_t s_{t+1}, \tag{9}$$

where the subscript t indicates the daily generation of the variable (i.e. the daily stance of the deviation from the quarterly steady state) and the tilde above the expectation operator indicates boundedly rational, backward-looking expectations. Naturally, these backward-looking expectations depend on already collected information about the model variables. Since the DCP for the real variables (i.e. output and inflation) is of a quarterly frequency, expectations are also updated only once in a quarter, hence the subscript q in $\tilde{E}_q y_{q+1}$ and $\tilde{E}_q\pi_{q+1}$. On the other hand, data on the stock market is available on daily basis, expectation of stock price is therefore daily updated; hence the subscript t in $\tilde{E}_t s_{t+1}$. $\tilde{\beta}^d$ is the discount factor $\tilde{\beta}$ adjusted for a daily frequency. It is equal to $\tilde{\beta}^{\frac{1}{64}}$.[1]

Similar to the baseline scenario in Airaudo et al. (2015), the policy rate reacts to expected inflation and the expected stock price. It is straightforward to observe that the frequency of the policy rate depends on the value of ϕ_s: a non-zero value for ϕ_s implies that the policy rate is set on a daily frequency, while for $\phi_s = 0$, the policy rate is set once every quarter, as it is a function of expected price inflation only, which itself is – by assumption – updated only once every quarter.

Further, the technology shock process is specified as follows

$$z_t = \rho_z^d z_{t-1} + \iota_t\nu_t, \tag{10}$$

[1] Equivalently, one can calculate the steady state daily real interest rate, $r^d = (1+r)^{\frac{1}{64}} - 1$. Then, $\tilde{\beta}^d = \frac{1}{1+r^d}$.

where ι_t is a random process that takes the value of 1 with a probability $\frac{1}{T^q}$ and 0 with a probability $1 - \frac{1}{T^q} = \frac{63}{64}$, and $\rho_z^d = \rho_z^{\frac{1}{T^q}}$. This way, a shock occurs on average once per quarter, analogous to a standard quarterly frequency model (e.g. Airaudo et al. 2015) and its persistence is equivalent to the persistence assumed in the quarterly frequency version.

Randomizing the day within the quarter, when a shock may occur, enlarges the scope of relevance of studying day to day updates of the model economy rather than simply the quarterly frequency version. To see this clearly, observe how equations (7) and (8) state that a shock arriving at any day t has an immediate effect on the inflation rate and the stock price, respectively. The change in the latter also immediately affects aggregate output (see equation 6). Following that, as will be later discussed (see equations 14 and 20 below), the expected stock price reacts to a change in the stock price with a one day delay. Further, at a non zero value for ϕ_s, the policy rate reacts immediately to the change in the (expected) stock price (see equation 9). Output, inflation rate and the stock price are by turn instantly impacted, and so forth. Our mixed frequency model can capture these updates as they happen, and then capture the effect of the real data when it is collected and made available at the end of the quarter. A homogeneous frequency (i.e. quarterly) model assumes that all these updates happen at a single point in time, and is unable to study such a gradual escalation in the dynamics portrayed here.

Finally, along the lines of e.g. De Grauwe (2011, 2012), we assume that agents are either targeters or naive regarding their expectations formation. Targeters expect a variable to return to its steady state value in the next period or, put differently, the variable's deviation from its steady state to be zero. On the other hand, naive agents expect the future value of a variable to be equal to the last known value for that variable. As within the days of a given quarter, data on the current quarter for output and inflation is unavailable, agents use the most recent available data, i.e. data on the last quarter, to make expectations about the next quarter, i.e.

$$\text{Targeting expectations: } \tilde{\mathrm{E}}_q^{\mathrm{tar}}[x_{q+1}] = 0, \qquad x \in \{y, \pi\}, \tag{11}$$

$$\text{Naive expectations: } \tilde{\mathrm{E}}_q^{\mathrm{naive}}[x_{q+1}] = x_{q-1}. \tag{12}$$

For the stock price, in contrast, agents can use the stock price of yesterday to make expectations concerning the stock price tomorrow:

$$\text{Targeting expectations: } \tilde{\mathrm{E}}_t^{\mathrm{tar}}[s_{t+1}] = 0, \tag{13}$$

$$\text{Naive expectations: } \tilde{\mathrm{E}}_t^{\mathrm{naive}}[s_{t+1}] = s_{t-1}. \tag{14}$$

The attractivity of a given heuristic A^j, $j \in \{\text{targeters}, \text{naive}\}$, is defined as a geometric sum of past squared expectation errors (cf. De Grauwe, 2010, 2011). Again, the quarterly availability of data for the real sector means that agents can evaluate the performance of a given heuristic only once per quarter. On the other hand a daily evaluation of the stock expectation heuristics is possible:

$$A_q^{x,j} = -\left(x_{q-1} - \tilde{E}_{q-2}^j x_{q-1}\right)^2 + \zeta\, A_{q-1}^{x,j}, \qquad x \in \{y, \pi\}, \tag{15}$$

$$A_t^{s,j} = -\left(s_{t-1} - \tilde{E}_{t-2}^j s_{t-1}\right)^2 + \zeta\, A_{t-1}^{s,j}, \tag{16}$$

where $0 \leq \zeta < 1$ is a memory coefficient. A lower value for ζ indicates a higher speed with which agents forget about the past.

As it is usual in the behavioral finance literature, the fractions of agents ω^j for the two heuristics are determined via a Brock and Hommes (1997, 1998) discrete choice approach (see also Westerhoff, 2012; Franke and Westerhoff, 2012; De Grauwe, 2011 and more recently, Kotb and Proaño, 2023):

$$\omega_q^{x,j} = \frac{\exp\left(\mu A_q^{x,j}\right)}{\exp\left(\mu A_q^{x,\text{tar}}\right) + \exp\left(\mu A_q^{x,\text{naive}}\right)}, \qquad x \in \{y, \pi\}, \tag{17}$$

$$\omega_t^{s,j} = \frac{\exp\left(\mu A_t^{s,j}\right)}{\exp\left(\mu A_t^{s,\text{tar}}\right) + \exp\left(\mu A_t^{s,\text{naive}}\right)}, \tag{18}$$

with μ being the intensity of choice parameter.

Market expectations are then given by a weighted average of the two heuristics:

$$\tilde{\mathrm{E}}_q\left[x_{q+1}\right] = \omega_q^{\mathrm{x,tar}} \tilde{\mathrm{E}}_q^{\mathrm{x,tar}}\left[x_{q+1}\right] + \omega_q^{\mathrm{x,naive}}\, \tilde{\mathrm{E}}_q^{\mathrm{x,naive}}\left[x_{q+1}\right], \tag{19}$$

$$\tilde{\mathrm{E}}_t\left[s_{t+1}\right] = \omega_t^{\mathrm{s,tar}} \tilde{\mathrm{E}}_t^{\mathrm{s,tar}}\left[s_{t+1}\right] + \omega_t^{\mathrm{s,naive}}\, \tilde{\mathrm{E}}_t^{\mathrm{s,naive}}\left[s_{t+1}\right]. \tag{20}$$

We now turn to the description of the assumed data collection process and how this feeds back into the expectations mechanism.

2.3 Data Collection Process under Temporal Aggregation

As the last day of a quarter q (i.e. day $t = 64 \cdot q$) is reached, data for that quarter is published. At this point, the last generated value for a variable represents its quarterly collected value,[2]

[2]See Bayar (2014) for insights on the outperformance of end of period values compared to average values in the monetary policy design. In our framework, end of period values are preferred to average values because

namely:

$$\text{DCP:} \quad y_q = y_{t=64\cdot q}, \tag{21}$$

$$\text{DCP:} \quad \pi_q = \pi_{t=64\cdot q}. \tag{22}$$

For the (unobservable) technology shock, the quarterly value can be thought of as the shock persistent from the last quarter plus the sum of newly arrived shocks within the quarter:

$$\text{DCP:} \quad z_q = \rho_z z_{q-1} + \sum_{t-63}^{t} (\iota_t \cdot \nu_t). \tag{23}$$

When data concerning the quarter has been collected, agents evaluate the attractivity of the different expectations heuristics, update their corresponding choices and take their economic decisions accordingly.

Despite its simplicity, this assumed DCP enables us to represent and highlight different important features. First, and foremost, the model explicitly accounts for mismatches between Data Generation and Data Collection processes. Such mismatches make studying the role of expectations even more relevant: how do expectations based on delayed information affect real, financial and monetary variables as they evolve from day to day, and vice versa? Second, in our model, an interest rate policy that targets the stock market does not need to wait for the new quarter to begin to react to stock price fluctuations, on which information is available on a daily basis. And third, as technology shocks can occur any day within a quarter, and not necessarily at the beginning of a new quarter, the discrepancy between the DCP and the DGP is even stronger. In the next section, we numerically study how these features interact, and compare the dynamics resulting from these interactions to the dynamics observed from the standard quarterly frequency model.

3 Model Analysis

3.1 Calibration

The baseline parameter values used in our numerical simulations are summarised in Table 1. Mostly, we adopt the calibration values of Airaudo et al. (2015). For the behavioural parameters, we follow Lengnick and Wohltmann (2016).

Temporal aggregation in our model is exemplary illustrated in Figure 1. The dotted lines

the first allow for decisions (e.g. expectations formation and policy rate setting) that are based on the exact stance of the real variables at the beginning of the new quarter rather than on average values from the previous

Table 1: Baseline simulation parameter values. ANZ (2015) stands for Airaudo et al. (2015), and LW (2016) for Lengnick and Wohltmann (2016).

parameter	Value	Source
Main parameters		
number of days per quarter	$T^q = 64$	LW (2016)
turnover ratio	$\gamma = 0.05$	ANZ (2015)
intertemporal discount factor	$\beta = 0.99$	ANZ (2015)
β adjusted for a positive turnover	$\tilde{\beta} = 0.96$	ANZ (2015)
elasticity of substitution between intermediate goods	$\epsilon = 2.3$	ANZ (2015)
the inverse of the Frisch elasticity of labor supply	$\chi = 0.25$	ANZ (2015)
Calvo price stickiness probability	$\theta = 0.91$	ANZ (2015)
ss of quarterly real interest rate	$r = 0.043$	ANZ (2015)
composite parameter κ	$\kappa = 0.011$	ANZ (2015)
composite parameter ψ	$\psi = 0.03$	ANZ (2015)
composite parameter λ	$\lambda = 0.0259$	ANZ (2015)
composite parameter φ	$\varphi = 0.047$	ANZ (2015)
composite parameter Ψ	$\Psi = 0.005$	ANZ (2015)
Monetary Policy		
coefficient of inflation	$\phi_\pi = 2$	ANZ (2015)
coefficient of stock price	$\phi_s = 0.0$	ANZ (2015)
Bounded Rationality, Learning		
Memory coefficient	$\zeta = 0.5$	LW (2016)
Intensity of choice	$\mu = 10$	LW (2016)
Technology Shock		
Shock Persistence (quarterly)	$\rho_z = 0.7$	LW (2016)
Standard deviation	$\sigma_z = 0.15$	LW (2016)
Stock Price Shock		
Shock Persistence (daily)	$\rho_\eta = 0.7$	LW (2016)
Standard deviation	$\sigma_\eta = 0.01$	LW (2016)

represent the day to day evolution of price inflation, output and the underlying technology shock. Given data collection and processing costs, this data is assumed not to be observable on a daily basis, and becomes only available to, or observable by, the public at the end of the quarter, in an aggregated form. The solid line corresponds to this quarterly published data. Further, as only quarterly figures of price inflation and output are in the information set of

quarter, which are no longer relevant (see Figures 1 and 2 for a visual illustration). Further, end of quarter values are consistent with our assumption regarding the data generation process (see Section 2.2).

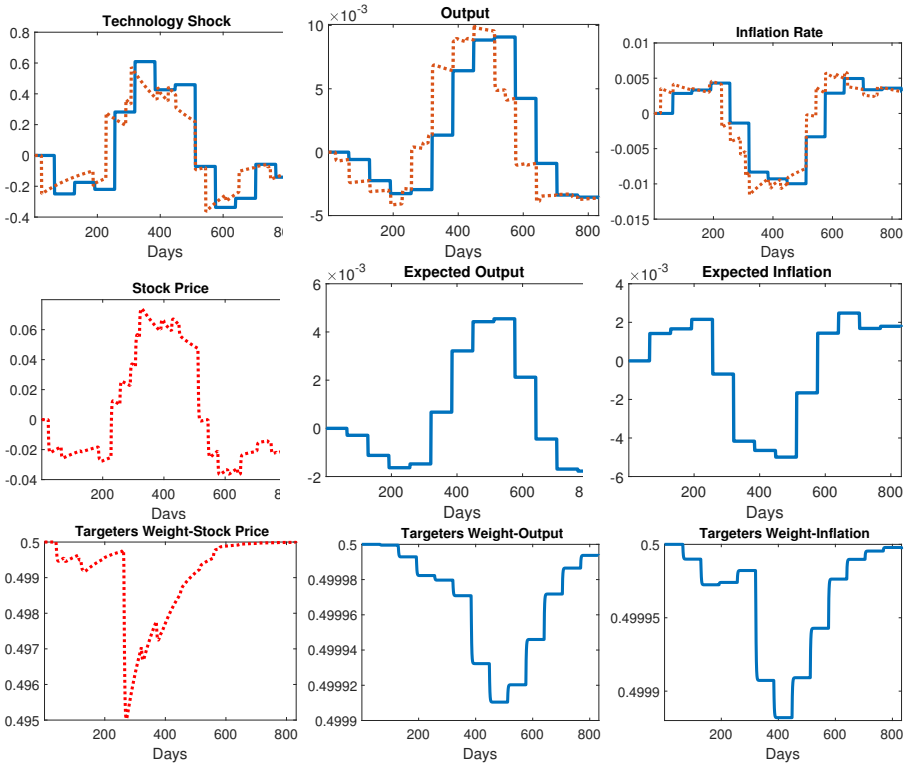


Figure 1: Temporal aggregation in the real sector. The dotted line shows the day-to-day generation of the variable. The solid line shows the quarterly collected values.

the agents, expectational rules of thumb (equations 11 and 12) are only updated once at the beginning of the quarter, delivering aggregate expectations of output and inflation, as well as updates to the weights associated with the different heuristics, of a quarterly frequency.

We assume that this temporal aggregation issue does not apply to financial market data, which is observable at the same frequency at which it is generated, namely a daily frequency. As a result, the expectations rules stated in equations (13) and (14) deliver aggregate stock price expectations (and switching behavior) that are also of a daily frequency.

In Figure 2, we illustrate the capability of our mixed-frequency framework to produce quarterly collected values that are comparable to the values obtained from the quarterly frequency model. More specifically, Figure 2 illustrates the IRFs (Impulse Response Functions) of the quarterly values of output, inflation and the technology shock from our mixed frequency model (the model as in equations (6) to (9)) as well as the quarterly frequency model (the model as in equations 1 to 4, under heterogeneous boundedly rational expectations) in response to a one standard deviation technology shock. As will be later explained in more

detail, a positive technology shock induces a positive reaction by output and the stock price, and a negative reaction by the inflation rate. As it can be observed, both representations of the model deliver results that are qualitatively, and to some extent quantitatively, similar. However, the delayed and incomplete information availability that characterises the mixed-frequency framework, causes a (seemingly)[3] weaker response of the model variables to the shock, compared to the quarterly frequency framework where information is complete and always "delivered on time".

Indeed, as we can observe in the figure, when the shock arrives on the last, rather than the first, day of the quarter, the effect of temporal aggregation is minimised and the quarterly values from our model are almost identical to those from a quarterly frequency model.

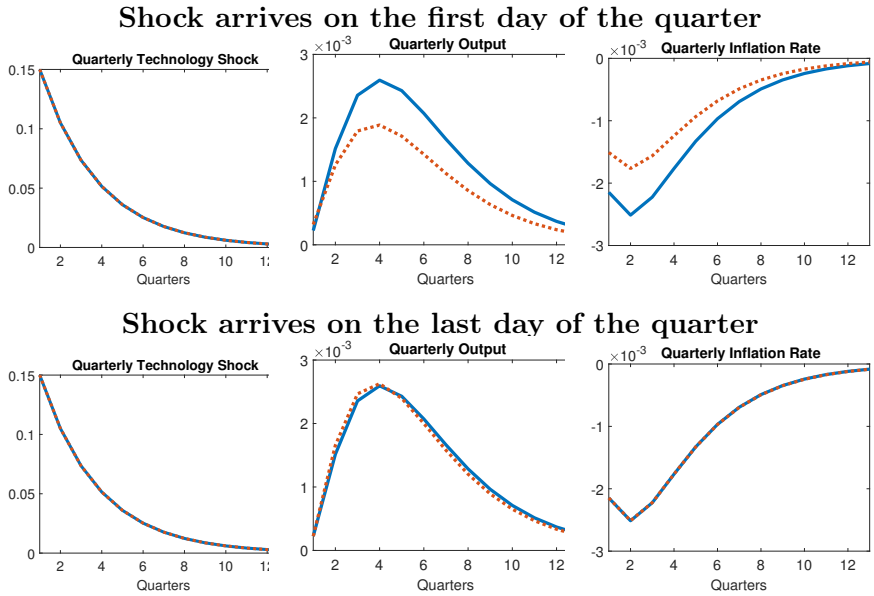


Figure 2: Impulse responses to a one standard deviation technology shock. The solid line represents the quarterly frequency model. The dotted line represents the mixed frequency model.

3.2 The Role of Expectational Rules-of-Thumb

Figure 3 illustrates the dynamic adjustments of the quarterly-frequency model variables to a one standard deviation technology shock under different values for the turnover ratio γ (0,

[3]"Seemingly" in the sense that these response graphs show only what is *collected*, not what is actually *generated*.

0,05 and 0.13)[4] for two cases: 1) rational (forward-looking) expectations and 2) boundedly rational (backward-looking) expectations as specified in Section 2.2.

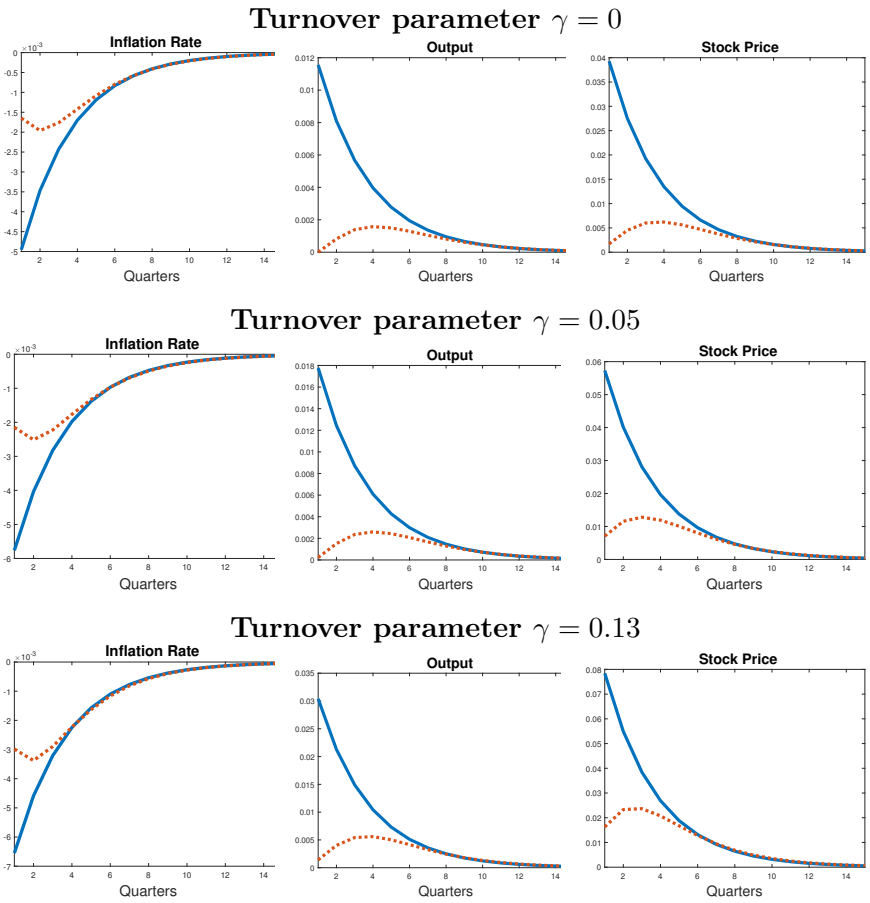


Figure 3: Impulse responses of the quarterly model variables to a one–standard-deviation technology shock, with rational expectations represented by the solid line and backward-looking expectations by the dotted line.

When the turnover ratio is equal to zero, the FWC does not exist; the shock affects output solely through the policy rate reaction to the inflation rate; stock price movements have no effect on output and therefore there is no rationale for the monetary policy to react to stock price developments. At a positive turnover ratio, the effect of a technology shock on the model variables is strengthened through the FWC: output is affected both by the policy rate and stock price movements, as illustrated in the second and third rows in Figure 3.

Backward-looking boundedly rational expectations significantly weaken the technology

[4] Airaudo et al. (2015) restrict their analysis to the range [0, 0.13] for the value of γ, with a benchmark of $\gamma = 0.05$.

shock impact on the model: regardless of the value of the turnover ratio, the real and financial reactions to the technology shock are mild, compared to the scenario with rational expectations. This can be attributed to the stabilizing effect of the targeting expectations. To illustrate this more clearly, Figure 4 shows the quarterly model's dynamic adjustments under the assumption of only naive (no targeting) expectations, i.e. $\tilde{E}_q x_{q+1} = x_{q-1}$, where $x \in \{y, \pi, s\}$. As it can be clearly observed, for $\gamma = 0$ (no FWC), an exogenous technology shock triggers cyclical dynamics that only slowly fade out in absence of the stabilizing targeting expectations and with only the more persistent (purely backward-looking) naive expectations.

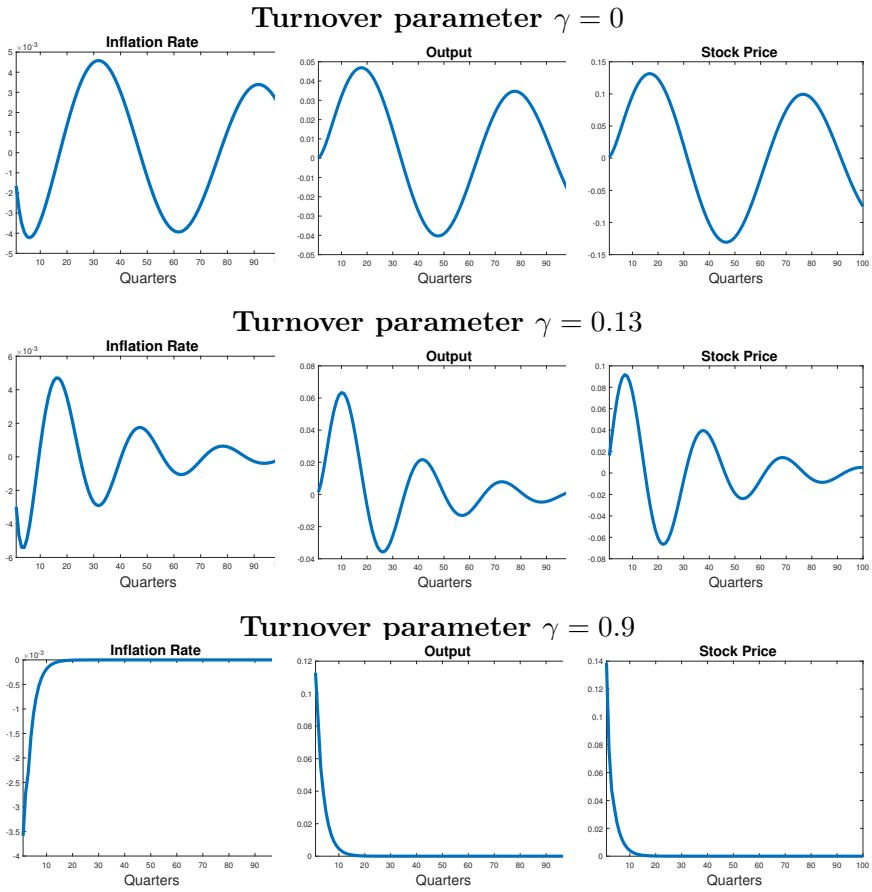


Figure 4: Impulse responses of the quarterly-frequency model variables to a one standard deviation technology shock under naive expectations.

We can observe that the FWC works in opposite direction to the backward-looking, naive expectations: the higher the value of the turnover ratio, the less cyclical the reaction to the shock is, and the sooner it fades out. At $\gamma = 0.9$, there are no cyclical dynamics, the model

variables monotonically return to the steady state following the initial reaction, despite the fact that only naive expectations are considered. The reason for this, is that the turnover ratio not only influences the direct effect of stock prices on the output gap (positively) – given by the term $\frac{\psi}{1+\psi}$ in equation (6) – but also (negatively) influences the effect of expected output gap and real interest rate per the term $\frac{1}{1+\psi}$ in equation (6). In other words, a high turnover ratio can counteract the destabilizing effect of naive expectations in the model but, at the same time, may also decrease the effectiveness of the traditional interest rate channel of monetary policy.

4 The Performance of a Daily Leaning against the Wind Policy under Temporal Aggregation

4.1 Targeting the Stock Price: Daily vs Quarterly Values

We begin by addressing the question of whether the policy rate should react to daily stock price fluctuations or, instead, whether it should use aggregate quarterised values, e.g. the average (expected) stock price in a quarter. For this purpose, we perform a Monte Carlo experiment to obtain simulated variances of the key variables of the model.

Figure 5 illustrates the result of a Monte Carlo experiment of 10,000 runs under different values for the policy parameters ϕ_π and ϕ_s. The rest of the parameters have the values of the baseline calibration as described in Table 1. Variances of (generated values of) output, inflation rate and the stock price are illustrated under three different modelling scenarios: First, the quarterly frequency model (basically, the model as in equations (1) to (4) under bounded rationality); second, our mixed-frequency version of the model (the model as in equations 6 to 9) with daily reaction to the expected stock price (i.e. $\phi_s \tilde{E}_t s_{t+1}$) and third, the mixed-frequency model with quarterly reaction to the expected stock price (i.e. $\phi_s \tilde{E}_q s_{q+1}$).[5]

The first pronounced feature of Figure 5 is the great similarity between the first two scenarios (i.e. first two rows): small values of ϕ_s (namely $\phi_s \approx 0.2$) stabilise both the stock price and output; higher values of ϕ_s further stabilise the stock price at the expenses of higher variability in output and inflation; higher values of ϕ_π stabilise the real sector with a slight loss in the stability of the stock price. By contrast, the third scenario delivers completely different results: On the one hand, the value of ϕ_s has a trivial effect on the stability of the real or financial variables. On the other hand, a strong reaction to inflation (illustrated by

[5]To achieve consistency, s_q is calculated similarly to y_q and π_q, and $\tilde{E}_q s_{q+1}$ is calculated similarly to $\tilde{E}_q y_{q+1}$ and $\tilde{E}_q \pi_{q+1}$.

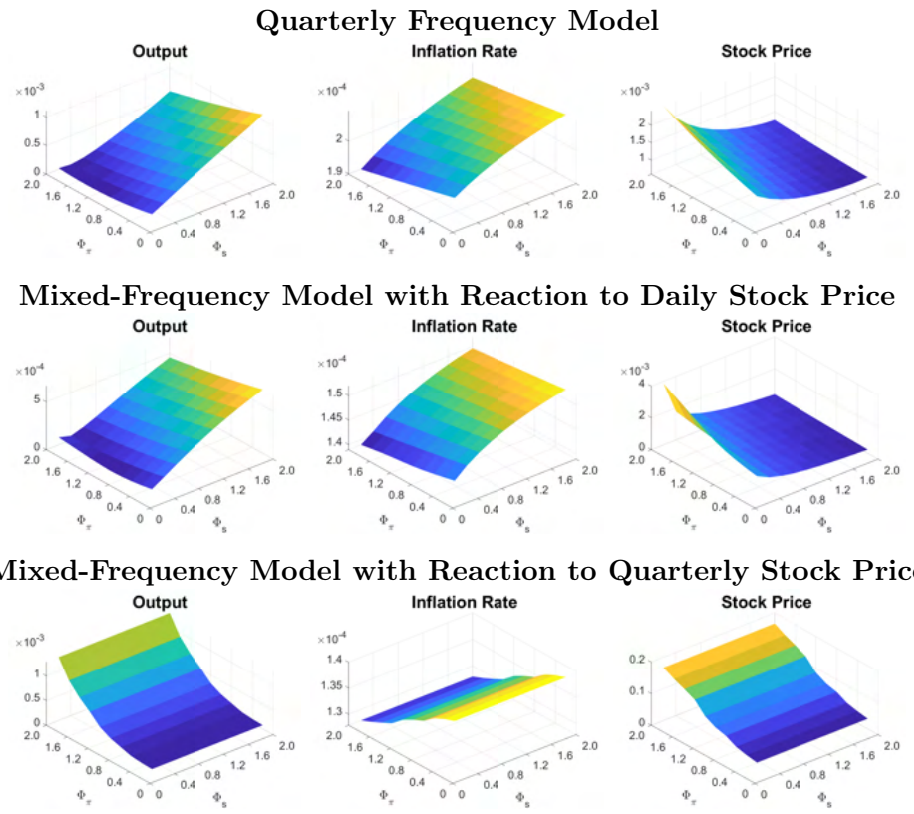


Figure 5: The variances of output, inflation and the stock price at different values for the policy parameters ϕ_π and ϕ_s, based on 10.000 Monte Carlo simulations. Rows from top to bottom present the quarterly frequency model, the mixed frequency model with the policy rate targeting daily (expected) stock price values, and the mixed frequency model with the policy rate targeting quarterly (expected) stock price values, respectively. Simulation length is 40 quarters (2560 days) and $\sigma_z = 0.5$.

high values of ϕ_π) greatly stabilises inflation but simultaneously destabilises the stock market. That, in turn, leads to output instability.

This result can be explained as follows: when the policy rate is strongly reacting to inflation without properly reacting to stock prices (i.e. a delayed reaction due to the quarterly frequency of the reaction), the stock market is made unstable (see equation 8). The positive effect of the stabilised inflation rate on the stability of output is outweighed by the negative effect of the unstable stock prices. Aggregate output is thus destabilised as a result of a policy rate that strongly targets inflation rate without properly reacting to stock price fluctuations.

The similarity between the first and second cases delivers a focally significant point: in our mixed frequency model, in which data collection mismatches in the real sector exist, a policy

rate that reacts to the daily available information on the stock price can successfully stabilise the stock market and to some extent neutralise the effect of such a data mismatch in the real sector. This success is to the extent that the model can deliver results that are similar to the scenario in which data collection mismatches are ignored altogether and a homogeneous frequency concerning data generation and collection for both the real and the financial sectors is assumed.

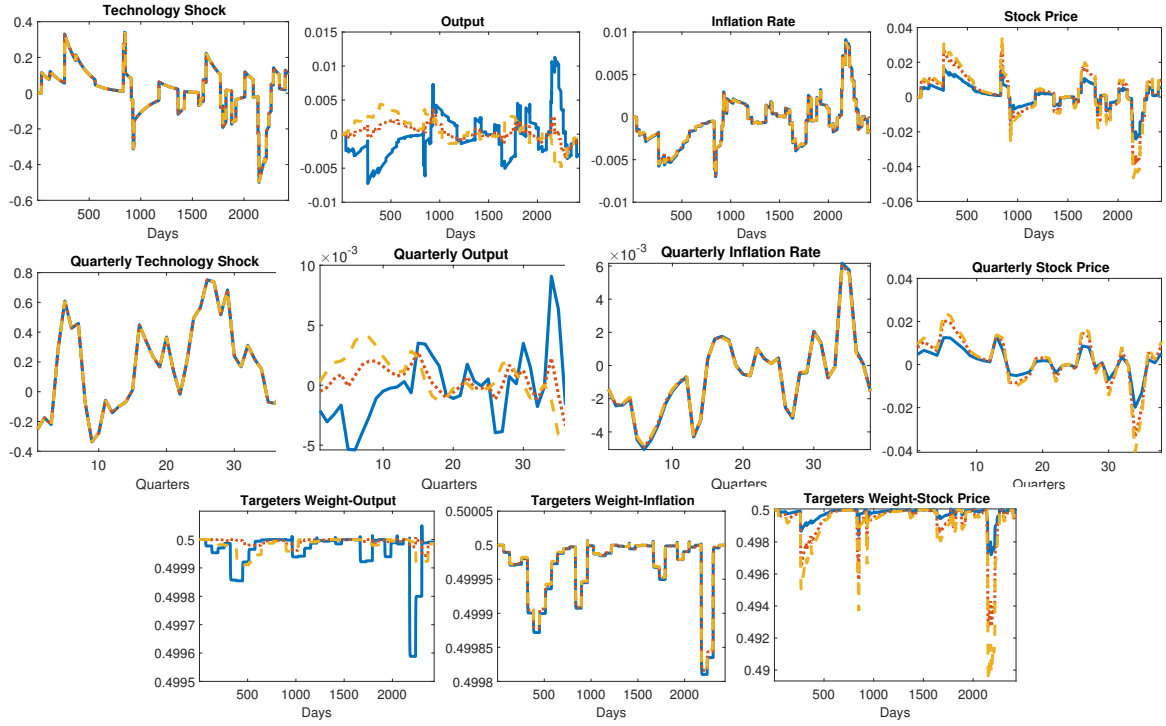


Figure 6: A simulation of the mixed frequency model with a daily reaction to the stock price. The solid line represents a relatively strong reaction to the stock price (ϕ_s =1). The dotted line represents a moderate reaction to the stock price (ϕ_s =0.2). The dashed line represents no reaction to the stock price ($\phi_s = 0$). Simulation length is 40 quarters (2560 days)

In Figure 6 we illustrate in more detail the effect the value of ϕ_s has on the dynamics of the model and the stability of both the real and the financial sectors, particularly in response to a technology shock. Therein the simulation results of our mixed-frequency model with daily reaction to stock prices for 40 quarters (2560 days) under three different policy scenarios: a) no reaction to the stock price ($\phi_s = 0$, dashed line), b) a moderate daily reaction to the expected stock price ($\phi_s = 0.2$, dotted line) and c) a strong daily reaction to the expected stock price ($\phi_s = 1$, solid line).

As we can observe, when the policy rate does not react to the stock price, output and the

stock price are relatively synchronised with the technology shock, whereas inflation moves in the opposite direction. This result is not surprising; better technology means lower prices, higher production and more appreciated stocks. At the other end of the policy spectrum, a strong reaction of the policy rate to the stock price highly stabilises the stock market at the expense of a highly unstable output which now moves in the opposite direction to technology updates. In other words, the effect of the strong reaction of the policy rate to stock prices outweighs the effect of the technology shock that it leads output to negatively co-move with technology.

A moderate policy reaction delivers optimal results in terms of output stability: output can be observed relatively close to the steady state all over the time line. At the same time, such a policy moderately stabilises the stock price: the dotted line, which corresponds to this moderate policy, falls between the solid line, which corresponds to strong reaction to the stock price and the dashed line, which corresponds to no reaction to the stock price.

The analysis of the attractiveness of the targeters' expectations, as reflected by the associated weights, is straightforward. When the variable deviates significantly from its steady state, the targeters' heuristic becomes less attractive (receiving a lower weight). Conversely, when the variable remains close to the steady state, the heuristic is more attractive (receiving a higher weight). As will be emphasized later, both the weights associated with each heuristic and the switching behavior are crucial for the stability of the model. Specifically, high-intensity switching, combined with large shocks and/or unstable stock prices due to the absence of stock price targeting, can lead to explosive dynamics. In contrast, less intense or minimal switching produces stable dynamics, even in the presence of large shocks.

Figure 7, which shows the model's dynamic adjustments to a one standard deviation technology shock, delivers analogous results: While a strong reaction to the stock price highly stabilises the stock market and more than offsets the positive effect of technology on output, a moderate reaction to the stock price fairly stabilises the stock market and provides the most stabilised output levels. These findings reinforce the insights we gained from the previous exercise: when intra-quarter data on inflation and output is not available, the policy rate can successfully stabilise the real sector together with the stock market by moderately reacting to stock prices.

Notice that, as shown in equations (11) and (15), the attractiveness of the targeters' heuristic is backward-looking, relying on data from the previous quarter. This is illustrated in the figure: when the policy rate responds strongly to the stock price, output falls below its steady state. Consequently, the attractiveness of the targeters' heuristic drops with a delay,

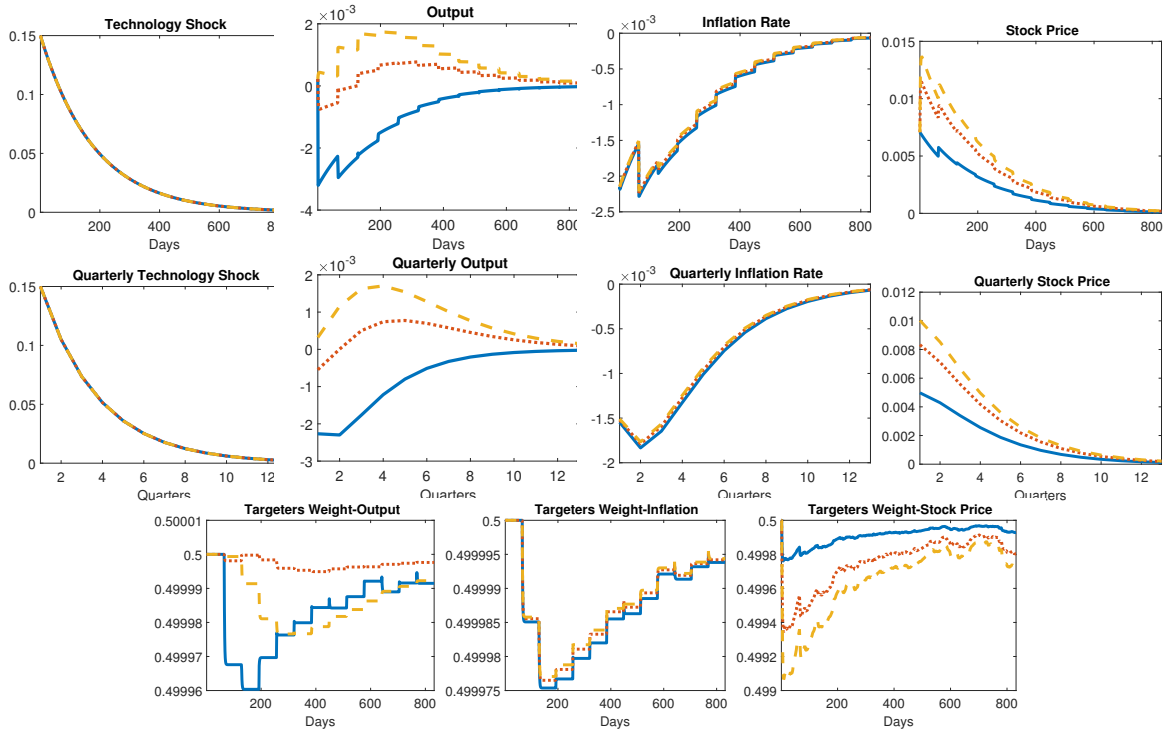


Figure 7: Impulse responses of the mixed frequency model with a daily reaction to the stock price to a one standard deviation technology shock. The solid line represents a relatively strong reaction to the stock price (ϕ_s =1). The dotted line represents a moderate reaction to the stock price (ϕ_s =0.2). The dashed line represents no reaction to the stock price ($\phi_s = 0$).

once the quarterly data reflecting the output decline are collected. As output returns to its stable path, the targeters' heuristic regains gradually its attractiveness.

To answer the question of to what extent leaning against daily stock price updates would be justified when a shock occurs relatively late in the quarter—i.e., when the next data release is imminent—we focus on the impulse responses of the model's variables to a one-standard-deviation technology shock that hits on the last day of the quarter. We consider three scenarios: no policy reaction to the stock price, a policy reaction to daily stock prices, and a policy reaction to quarterly-aggregated stock prices (see Figure 14 in the Appendix). Even in this late-quarter scenario, a daily policy reaction still produces more stable output and stock prices. This is due to both the on-impact policy response and the continued reaction to the persistent shock, which continues to affect the economy in the days following the initial disturbance.

Figure 8 shows the variance of output for different combinations of the switching param-

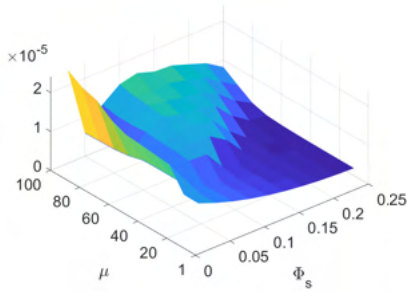


Figure 8: Variance of output for different values of the policy parameter ϕ_s and the switching parameter μ, based on 10.000 Monte Carlo simulations. Each simulation spans 40 quarters (2,560 days), with $\sigma_z = 0.15$.

eter μ and the leaning parameter ϕ_s. We capped ϕ_s at 0.25 to capture the stability benefit of increasing stock price targeting from zero to a moderate level (around 0.2). As expected, a higher switching parameter leads to greater output variation, while moderate leaning contributes to stability. In general, a combination of a high switching intensity and low or no reaction to the stock price increases output variance.

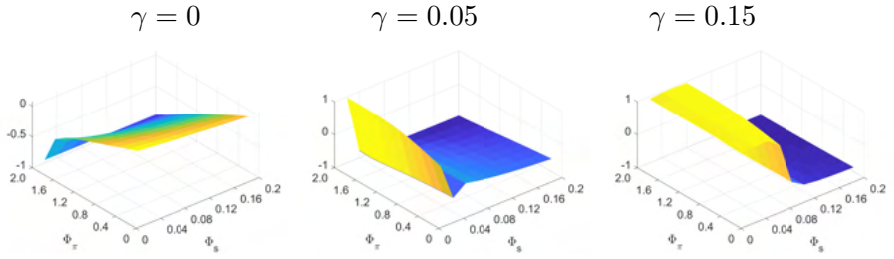


Figure 9: Correlation between output and the stock price under three different values of the turnover ratio γ: 0 (first row), 0.05 (second row), and 0.15 (third row). The standard deviation of the technology shock is set to $\sigma_z = 0.5$.

Figure 9 shows the correlation between output, y, and the stock price, s, for different values of the turnover ratio, γ. When $\gamma = 0$, i.e., the FWC does not exist, the correlation between s and y is close to zero, except in the case of a strong reaction to the inflation rate. To explain that, consider, for example, a positive technology shock, which increases the stock price and reduces inflation. A strong policy reaction to inflation then reduces output, resulting in a negative correlation with the stock price. With positive turnover, if the policy does not respond to the stock price, the correlation between output, y, and the stock price, s, is positive, reflecting the effect of the FWC. However, if the policy reacts positively to the

stock price, output becomes progressively less sensitive to technology shocks, or may even move in the opposite direction to the shock (and the stock price), as illustrated earlier. As a result, the correlation between y and s can turn negative.

4.2 Output vs. Stock Price Stabilization

Figure 10 displays the results for the case where the forward-looking policy rule also responds to expected future output, that is,

$$r_t = \phi_\pi \tilde{E}_q \pi_{q+1} + \phi_s \tilde{E}_t s_{t+1} + \phi_y \tilde{E}_q y_{q+1},$$

for the mixed frequency model and

$$r_q = \phi_\pi \tilde{E}_q \pi_{q+1} + \phi_s \tilde{E}_q s_{q+1} + \phi_y \tilde{E}_q y_{q+1},$$

for the quarterly frequency model, for three different values for the turnover ratio γ: 0, 0.05 and 0.13.

By observing output variance of the quarterly frequency model (first row), one can notice that the value of ϕ_y that achieves the most stable output (lowest variance) decreases, the stronger the FWC (i.e. the higher the value of γ) is, and that at any value for the policy parameters, output is more volatile at higher values for γ. The FWC narrows the scope for output response by the policy rate and increases the validity of responding to the stock price. This is in line with the findings of Airaudo et al. (2015), and with our discussion of Figure 4.

The second row, which presents the mixed-frequency model, delivers considerably different results. First, responding to output is fairly ineffective in stabilizing output. Put differently, temporal aggregation, which means that the policy rate can only respond to quarterly updated output expectations, negatively influences the effect of such a response on the output volatility. Second, responding to the stock price, upon which data is available daily, is not irrelevant for output volatility. Even at $\gamma = 0$, i.e. no FWC, a policy response to the stock price is still an effective tool to stabilise output, since when intra-quarter real data is not available, stock price movements reflect unobserved real fluctuations and/or events (e.g. the arrival of a technology shock). Under these circumstances, a moderate policy reaction to the stock price is also, indirectly, a reaction to output. Recall that, as previously illustrated in Figures 6 and 7, at low values for ϕ_s, there is a positive comovement between output and stock prices in response to technology shocks.

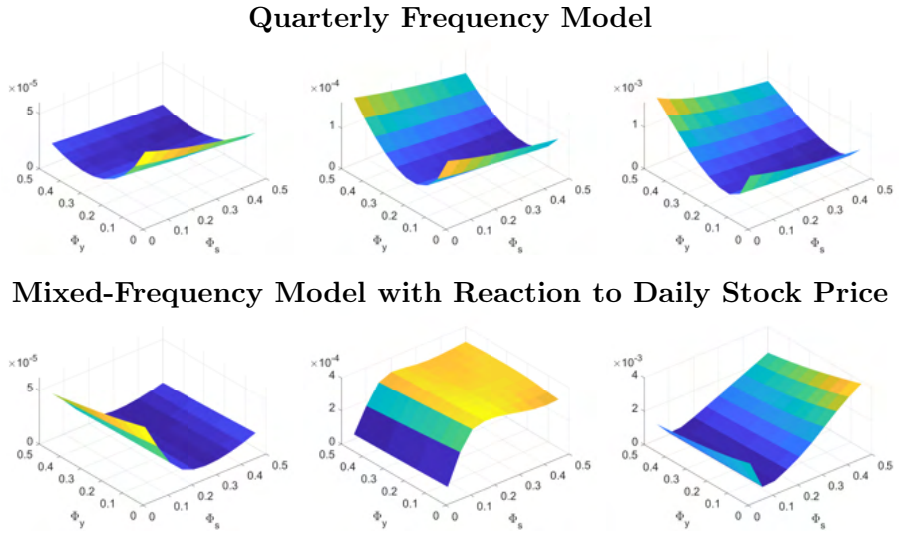


Figure 10: Output variances under three different values for the turnover ratio based on 10.000 Monte Carlo simulations. Columns from left to right show $\gamma = 0$, $\gamma = 0.05$ and $\gamma = 0.13$, respectively. Simulation length is 40 quarters (2560 days).

4.3 Leaning against the Wind under Cost-Push and Stock Price Shocks

We now consider the robustness of the results when the model includes additional shocks, specifically a cost-push (inflation) shock and stock price disturbances. To investigate this, we revisit equations (7) and (8) as follows:

$$\pi_t = \tilde{\beta}\tilde{E}_q\pi_{q+1} + \kappa(1+\chi)(y_t - z_t) + \upsilon_t, \tag{24}$$

$$s_t = \tilde{\beta}^d\tilde{E}_t s_{t+1} - \lambda\tilde{E}_q y_{q+1} - (r_t - \tilde{E}_q\pi_{q+1}) + \varphi z_t + \eta_t. \tag{25}$$

The variable $\eta_t = \rho_\eta \cdot \eta_{t-1} + \xi_t$ represents an AR(1) stock price shock, where $\rho_\eta \in (0,1)$ and ξ_t is an i.i.d. disturbance. The variable υ_t is a cost-push shock that follows a structure similar to the technology shock (see equation 10 and the accompanying explanation). In this way, we introduce an additional quarterly shock to the real sector, alongside daily stock price noise.

The exercise in Figure 11 is analogous to that in Figure 5, but considers the case of a cost-push shock (with a standard deviation, $\sigma_\upsilon = 0.01$) rather than a technology shock. The results are also quite similar: a moderate reaction to daily stock price updates stabilises both output and the stock price, much like a reaction to the quarterly stock price in the quarterly-frequency model. In contrast, a reaction to the aggregated stock price does not yield any

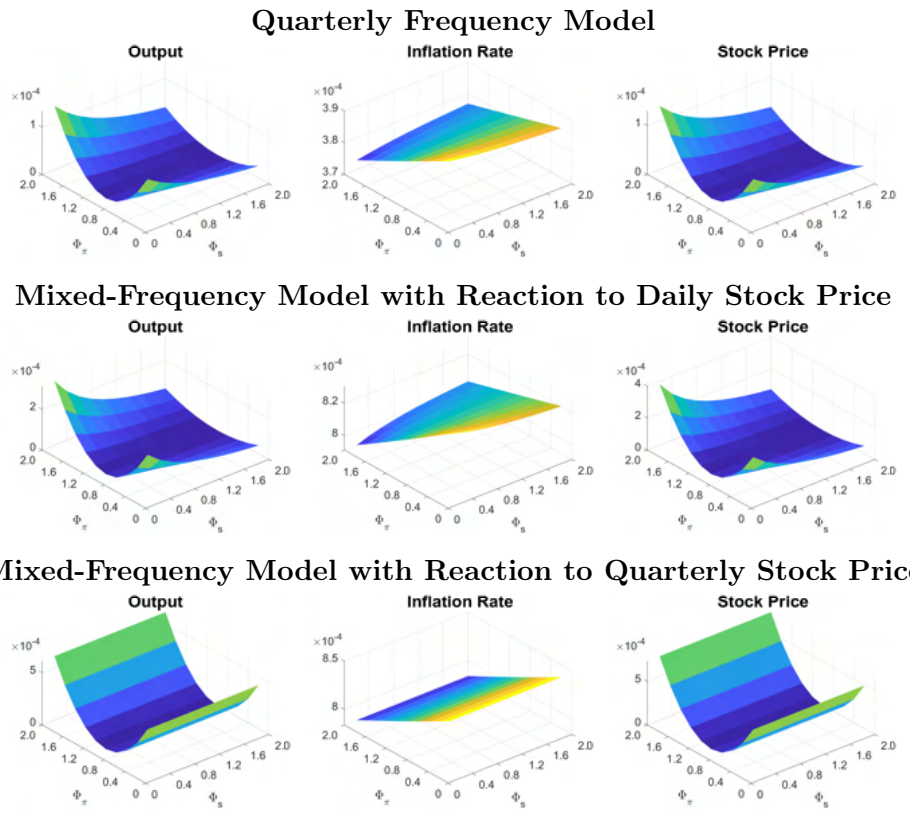


Figure 11: The variances of output, inflation and the stock price at different values for the policy parameters ϕ_π and ϕ_s, based on 10.000 Monte Carlo simulations. Rows from top to bottom present the quarterly frequency model, the mixed frequency model with the policy rate targeting daily (expected) stock price values, and the mixed frequency model with the policy rate targeting quarterly (expected) stock price values, respectively. Simulation length is 40 quarters (2560 days) and the standard deviation of the cost-push shock ist set to $\sigma_\upsilon = 0.01$.

stabilising benefits.

The exercise is repeated with a higher standard deviation for the inflation shock, namely $\sigma_\upsilon = 0.1$. In Figure 12, where switching between heuristics is allowed and the switching parameter is set to its baseline value of $\mu = 10$, the model dynamics become explosive. When switching is turned off ($\mu = 0$), the model remains stable even under such a large shock. This is illustrated in Figure 13, which also shows a positive effect of daily stock price targeting on output stability.[6]

[6]In the appendix we report the impulse-response functions of the model in the face of a cost-push (Figure 15), illustrating the stabilizing effect of stock price targeting, as well as the dynamic adjustments following a stock price shock (Figure 16). There, a clear trade-off emerges between stock price stabilization and the

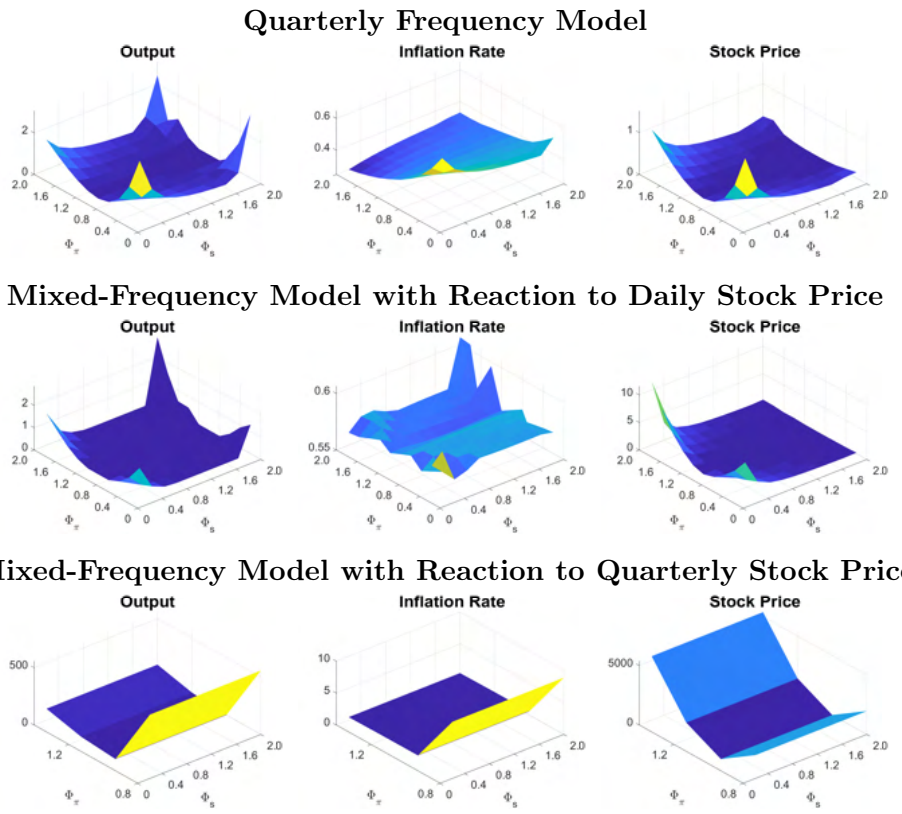


Figure 12: The variances of output, inflation and the stock price at different values for the policy parameters ϕ_π and ϕ_s, based on 10.000 Monte Carlo simulations. Rows from top to bottom present the quarterly frequency model, the mixed frequency model with the policy rate targeting daily (expected) stock price values, and the mixed frequency model with the policy rate targeting quarterly (expected) stock price values, respectively. Simulation length is 40 quarters (2560 days) and the standard deviation of the cost-push shock ist set to $\sigma_\upsilon = 0.1$.

stability of output, inflation, and the interest rate. In other words, when the source of the shock originates in the financial sector, maintaining a stable real economy requires the absence of leaning.

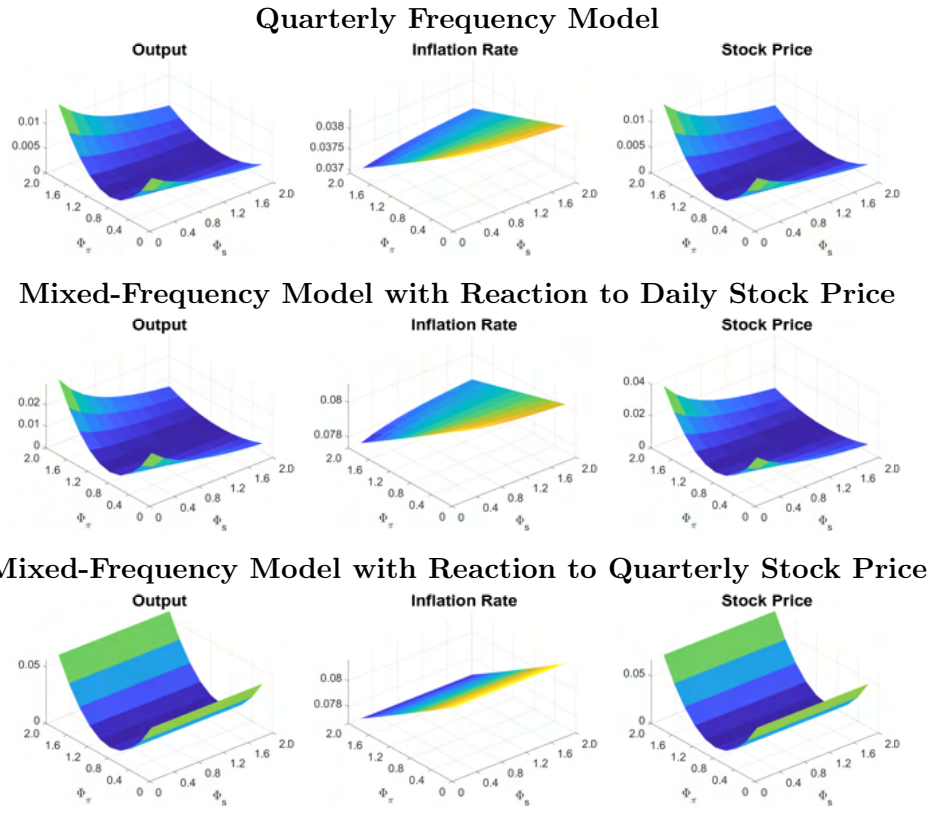


Figure 13: The variances of output, inflation, and the stock price at different values of the policy parameters ϕ_π and ϕ_s, based on 10.000 Monte Carlo simulations. Rows from top to bottom present the quarterly-frequency model, the mixed-frequency model with the policy rate targeting daily (expected) stock price values, and the mixed-frequency model with the policy rate targeting quarterly (expected) stock price values, respectively. Simulation length is 40 quarters (2,560 days); the standard deviation of the cost-push shock is set to $\sigma_\upsilon = 0.1$, and the intensity of choice is set to $\mu = 0$ (no switching).

5 Concluding Remarks

In this paper we revisited the question of whether the central bank should adjust the policy interest rate in response to stock price movements within a mixed-frequency macroeconomic model featuring boundedly rational expectations and a discrepancy between data collection and data generation processes. We showed that within our theoretical framework a moderate, high-frequency (i.e., daily) policy response to the stock price can play a significant role not only in stabilizing the stock market, but also the real sector, especially when real data are temporally aggregated. Furthermore, we illustrated the role of backward-looking (naive) and targeting expectations in shaping model dynamics compared to forward-looking rational expectations. Targeting expectations are highly stabilizing and weaken the spillover effect between the real and financial sectors relative to rational expectations, whereas naive expectations generate cyclical and persistent dynamics following an exogenous shock. Additionally, we demonstrated that the process of switching between different heuristics can produce explosive dynamics when accompanied by large shocks.

We stressed that when information about the shock or the real variables is not timely available (i.e. available only in an aggregated form and with a delay), the central bank indirectly targets these latter variables by reacting to the stock price observed at a high frequency. In such a context, the stock price acts as a proxy to the actual state of the economy. This concept has been previously emphasised by Gilchrist and Leahy (2002, p. 83): "Asset prices aggregate information from diverse sources in a timely matter and are obvious candidates to be proxies of the underlying state of the economy." While we do not argue for a daily revision or setting of the policy rate in the real world, our analysis does highlight the importance of mixed-frequency econometric techniques that allow to incorporate high-frequency financial market data into the assessment of the current state of the economy, and by extension the updating of expectations or forecast at more frequent intervals.

In the final part of our study, we showed that whether leaning against the stock price brings stabilizing benefits to the real sector depends on the origin of instability or the nature of the shock. When technology and inflation shocks are analysed, moderate leaning produces stable real dynamics. However, when the shock originates in the stock market, leaning unnecessarily transmits financial instability to the real sector. In that case, no reaction to the stock price results in greater stability of output, inflation, and the nominal interest rate.

A Additional Figures

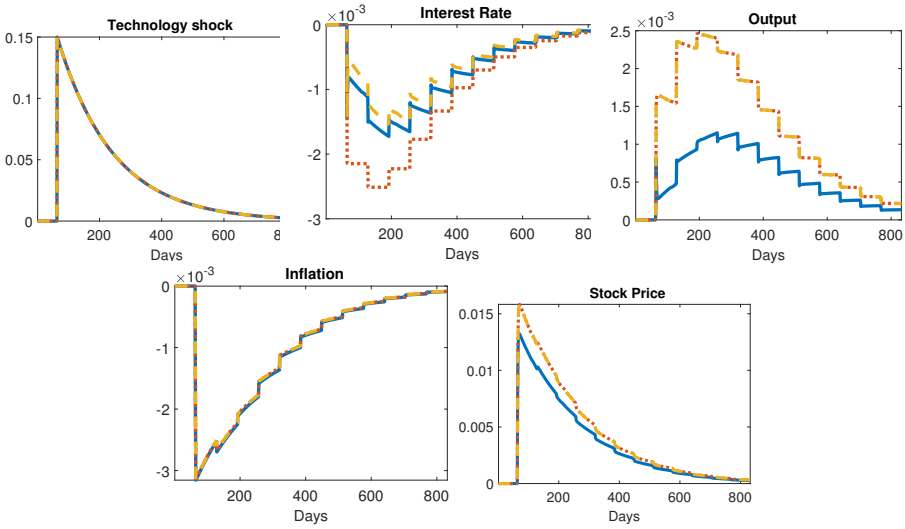


Figure 14: Impulse responses to a one-time technology shock occurring on the last day of the quarter. The solid line indicates the daily reaction to the stock price, the dotted line indicates no reaction to the stock price, and the dashed line indicates a reaction to the quarterly aggregated stock price.

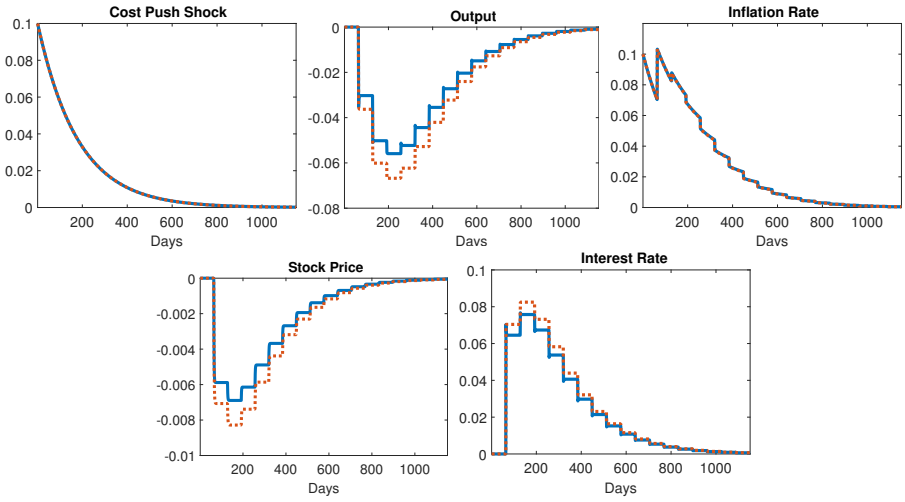


Figure 15: Impulse responses of the mixed-frequency model to a one-time cost push shock. The solid line represents a moderate reaction to the stock price ($\phi_s = 0.2$), while the dotted line represents a no-reaction policy ($\phi_s = 0$).

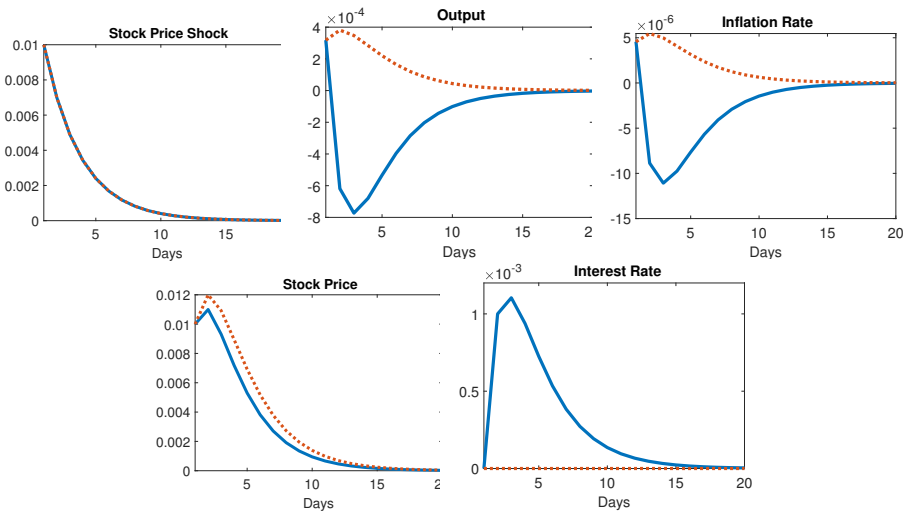


Figure 16: Impulse responses of the mixed-frequency model to a one-time stock price shock. The solid line represents a moderate reaction to the stock price ($\phi_s = 0.2$), while the dotted line represents a no-reaction policy ($\phi_s = 0$).

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