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Does the Cost of Private Debt Respond to Monetary Policy? Heteroskedasticity-Based Identification in a Model with Regimes

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Does the Cost of Private Debt Respond to Monetary Policy?

Heteroskedasticity-Based Identification in a Model with Regimes

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Abstract

We investigate the effects of a conventional monetary expansion, the quantitative easing, and maturity extension programs on the yields of corporate bonds. We adopt a multiple-regime VAR identification based on heteroskedasticity. An impulse response function analysis shows that a traditional, rate based expansionary policy leads to an increase in yields. The response to quantitative easing is instead a general and persistent decrease, in particular for long-term bonds. The responses generated by the maturity extension program are significant and of larger magnitude. A decomposition shows that the unconventional programs reduce the cost private debt primarily through a reduction in risk premia.

Keywords: unconventional monetary policy; transmission channels; heteroskedasticity; vector autoregressions; identification; corporate bond yields.

JEL code: G12, C32, G14

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"(…), the effects of LSAPs do not appear to be confined to longer-term Treasury yields. Notably, LSAPs have been found to be associated with significant declines in the yields on both corporate bonds and MBS. (…) It is probably not a coincidence that the sustained recovery in U.S. equity prices began in March 2009, shortly after the FOMC's decision to greatly expand securities purchases. This effect is potentially important because [these] values affect both consumption and investment decisions.
(B. Bernanke, Monetary Policy since the Onset of the Crisis, Speech at the Federal Reserve Bank of Kansas City Symposium, Jackson Hole, Wyoming, August 31, 2012)

1. Introduction

To what extent monetary policies may still affect the cost of private debt, for instance as expressed by the yields implied by the market prices of corporate bonds, in times of financial distress and volatile asset prices? In this paper we investigate this key question to policy making and to the very understanding of the performance of modern market-based economies using statistical methods that indeed exploit the very conditions of distress and volatile asset prices to (arguably) achieve a causal identification of monetary policy shocks, to assess their net, effective impact on the cost of private debt.

The Great Financial Crisis (GFC) has posed unprecedented challenges to the U.S. Federal Reserve (henceforth, the Fed), questioning the conventional wisdom that generally guides monetary authorities (see, e.g., Joyce et al., 2012). Indeed, already in December 2008, the zero lower bound for the Fed funds rate was reached, and this forced the Fed to turn to alternative policies. Starting in late 2008, the Fed purchased massive amounts of assets with medium and long maturities (see Gagnon et al., 2011), primarily agency bonds and mortgage-backed securities (MBS).[1] These policies, which imply the increase of the monetary base through the direct purchase of fixed income securities with long term to maturity, are generally known as Quantitative Easing (henceforth, QE). In addition to those purchases, in September 2011 the Federal Open Market Committee (henceforth, FOMC) launched the Maturity Extension Program (MEP), a policy that consists of the purchases long-term Treasury securities financed by the contemporaneous sales of an identical amount of short-term notes, for a total worth of $400 billion. In contrast to QE, the MEP, also known as Operation "Twist" (OT) keeps the monetary

[1] These purchases have been called Large-Scale Asset Purchases (LSAPs) and they have been implemented in two subsequent steps. The so-called LSAP1 started in November 2008, when the Fed announced purchases of housing agency debt and agency MBS of up to $600 billion. The subsequent LSAP2 was put in place in March 2009, when the FOMC decided to expand its purchases of agency-related securities and to start purchasing longer term Treasury securities, for a total of $1.75 trillion.

base constant, but induces a change in the relative supply of long- and short-term Treasury securities, through a change in the composition of the balance-sheet of the Fed.

The minutes of the FOMC meeting of December 15-16, 2008 stated that the purpose of these unconventional policies was to "(...) support overall market functioning, financial intermediation and economic growth" since the purchases were expected to"(...) reduce borrowing costs for a range of private borrowers", i.e., the yields of those debt instruments that are issued by firms to satisfy their financing needs, such as corporate bonds. Considering the objectives of the Fed and the general importance of debt financing for U.S. firms, it is particularly relevant to understand the effects of conventional and unconventional monetary policies on corporate bonds. This is exactly what our paper does, using standard tools from structural vector autoregression analysis but also applying a non-recursive, heteroskedasticity-based identification scheme that is particularly suitable to an analysis of the propagation of shocks in financial markets (where, on the opposite, standard Cholesky scheme may lie on thin logical grounds, see Canova and de Nicolò, 2002, Gertler and Karadi, 2015) as it allows the estimation of different on-impact responses in each volatility regime. In essence, we ask whether the idea that a shock to the level and the slope of the Treasury yield curve, such as the one that the monetary authority was able to produce by means of unconventional policies (see, among the others, Gagnon et al., 2011; Hamilton and Wu, 2012; Krishnamurthy and Vissing- Jorgensen, 2012), be transmitted to corporate yields and spreads (at least in a crisis regime) finds support in the data: what type of evidence may have led the Fed to pursue aggressive QE and duration/maturity management programs between 2008 and 2014, given the goals stated in the very FOMC minutes? Can we provide support to an expectation that the cost of private debt capital would have been lowered and expansionary unconventional shocks be correctly transmitted in the data then (and now) available? As noted by Gilchrist and Zakrajšek (2013), this task is complicated by the simultaneity of policy decisions and movements in the prices of risky financial assets, as well as by the fact that both the corporate yields and the spreads (the risk premia) targeted by unconventional monetary policy reacted to other common shocks during the financial crisis.

There is now an extensive literature that has investigated the ex-post effect (as well as effectiveness, often using an implicit "bang-for-the-buck" approach) of QE and the MEP on the securities that were purchased by the Fed as well as on the assets that were not purchased directly. The majority of those studies found that LSAPs and MEP were successful at lowering the Treasury yields and the yields of the other assets under purchase (agency debt and mortgage-backed securities), while the effects on assets that were not purchased directly remain more controversial (see, e.g., Justiniano et al., 2012; Rogers et al., 2014; Stroebel and Taylor, 2012). Both Krishnamurthy and Vissing- Jorgensen (2012) and Gagnon et al. (2011) found that LSAP1 induced a decline in the 10-year Treasury yield of 100 bps and 91 bps, respectively. LSAP2 was studied, among others, by Greenwood and Vayanos (2014), Krishnamurthy and Vissing-Jorgensen (2012), D'Amico et al. (2012), Meaning and Zhu (2011), and Swanson (2011), to find a reduction in Treasury yields in a range between 15 bps and 55 bps. Most of these papers perform event studies (see Gürkaynak and Wright, 2013) supplemented by regressions to control for covariates and confounding effects, and therefore assume that the unconventional measure announcements can be taken as exogenous to the variables under scrutiny. In the case of MEP, Hamilton and Wu (2012) found that Treasury yields with maturity in excess of 2 years fell by about 17 bps, while short-term Treasury yields increased by a similar amount.

Differently from this body of research, our goal is to investigate the effects that conventional monetary policy, QE, and the MEP on the yields of corporate bonds with different maturities and ratings in different regimes. As anticipated, on this margin the literature is thinner and even when evidence has been reported of an effect of QE and MEP on the cost of debt capital to firms, such evidence is weak, with relatively modest medium-term policy multipliers after parameter uncertainty is taken into account, as in Guidolin et al. (2017). Our approach differs from many of the earlier studies in two ways. First, instead of performing event studies that are informative on an ex-post basis, we estimate a regime-switching structural vector autoregressive (SVAR) model and base our analysis on an identification scheme that relies on heteroskedasticity (IH) (in a first-pass reduced form VAR residuals) proposed by Rigobon (2003) and Lanne and Lütkepohl (2008), instead of more traditional, recursive Cholesky scheme that rely on imposing an ordering of the contemporaneous effects among variables that appears to be problematic when applied to weekly interest rates. This choice is crucial. Using a rich set of simulations, Herwartz and Plodt (2016) have shown that IRFs identified by means of (co)variance shifts offer the most precise measures of the true dynamics and that, as expected, the performance of the identification via IH depends on the relative size of the volatility shifts (that should be large) and the length of the sample at hand (that should exceed 200 observations). Our application appears to fulfil the requirement reported by Herwartz and Plodt to support an IH identification scheme. Importantly, resorting to alternative regimes in our case is not just an identification device. Second, differently from the bulk of the literature, we pursue an a-priori investigation, instead of an ex-post assessment (for instance, see in Gagnon et al., 2011) of the effects of those monetary policies on securities that were not directly included in the purchase programs but which are the target of policy-makers, simulating the effects of each type of monetary policy through the use of impulse response function (IRF) analysis.[2]

[2] This claim requires, as it turns out to be the case, that the regime in conditional residual variances exploited to achieve identification did occur and showed sufficient persistence over sub-samples

Our results show that the responses of corporate bonds to the simulated, *unconventional* policies were likely perceived as rather effective, precisely estimated and leading to desirable response (i.e., a reduction in the cost of capital for firms, including those of relatively low credit standing) in all the regimes under analysis, in contrast to the relatively weak evidence reported in earlier work (e.g., by Guidolin et al., 2017) that use traditional, recursive identification schemes. However, it is the case also in our analysis that the estimated effects turned out to be stronger in a regime that is identified as describing a state of crisis and market turmoil. For instance, in our third, more volatile regime, the effect of a QE-type shock (an *unanticipated* decline in the 10-year rate) is a statistically significant decline of up to 14 bps and of 45 bps for investment grade and non-investment long-term yields, respectively. In the case of MEP shocks (an *unanticipated* decline in the 10-year rate accompanied by an *unanticipated* increase in the 1-year T-bill rate), the corresponding responses are a decrease of about 22 and 107 basis points, for investment and non-investment grade corporate yields, respectively. Further analysis within a SVAR identified with a similar heteroskedasticity methods shows that most of these hefty effects come from a reduction over time and precisely estimated of credit spreads, i.e., from a risk premium channel, using the classification put forth by Longstaff (2010).

In contrast with the objectives of policymakers, our analysis shows that a *conventional*, expansionary monetary policy would have led to a generalized increase, rather than a decrease, in corporate yields; such a perverse reaction of the cost of private debt might have been sizeable, e.g., an increase by about 80 bps for non-investment grade bonds and of the order of 20 bps for investment grade bonds, in the crisis state. This is in line with the findings of Guidolin et al. (2017) and it can be interpreted as a consequence of the inflationary expectations that short-term rate-based policies may trigger, i.e., the increase in corporate yields might be caused by higher inflation expectations (see Ang and Piazzesi, 2003).

These results are robust to different specifications of the model, obtained through the introduction of common shocks in the SVAR model, and to replacing the series of corporate yields with credit spreads (computed as a difference vs. maturity matched Treasuries, on an individual trade basis), which offers a complementary perspective on the simulated effects of conventional and unconventional Fed policies on the credit risk premium. Indeed, IRFs estimated from a SVAR applied to Treasury term spreads and corporate credit spreads leads to similar empirical estimates as those obtained from the baseline model, in contrast to earlier findings that especially MEP policies would be effective in simulation experiments but would cause mixed effects on risk

preceding 2008-2009 and of sufficient length. Gürkaynak and Wright (2013) explain how IH may represent a logical thread between classical VAR analysis and event studies: the temporarily, regime-specific higher variances are used as an instrument for exogenous news.

premia (see, e.g., Guidolin et al., 2017).

Two related papers are Gilchrist and Zakrajšek (2013) and Guidolin et al. (2017).[3] Gilchrist and Zakrajšek have estimated the effects of the Fed's QE and MEP programs on corporate credit risk by also employing a heteroskedasticity-based, event study approach to estimate the structural coefficient measuring the sensitivity of credit risk to declines in the benchmark market interest rates prompted by the unconventional monetary policy announcements. While they report that QE announcements led to a significant reduction in CDS indices for both investment- and speculative-grade corporate bonds, their analysis focuses on the GMM estimation of the impact of policy announcements and does not produce a full IRF analysis. Moreover, their analysis concerns only the sub-set of corporate entities for which credit risk derivatives are traded, while we base our estimation on aggregated indices of yields and spreads implicit in all transactions captured by the TRACE data repository. Guidolin et al. simulate the effects of a range of monetary policies in flexible SVAR models with regimes, identified using a range of Cholesky decompositions. They report that the responses of corporate bonds to unconventional monetary policies are statistically significant and of the sign intended by policy-makers only when implemented in the regime identified with the crisis state. However, in spite of the considerable robustness checks performed, whether or not the ordering implied by Cholesky identification schemes remain contentious. We depart from their set up of analysis by using an alternative identification scheme and by performing a rather detailed set of robustness checks on the effects of common shocks to the interest rate series trigged by changes in general economic conditions.

Section 2 introduces the data and describes the questions under investigation. Describing the data as a first step is also a way to make sure that our methodologies are specifically tailored to the application at hand. Section 3 describes our methods to deal with the method-of-moments estimation SVAR models. Section 4 reports our key empirical findings on IRF analysis that can be interpreted as a simulation exercises on the effectiveness of alternative policies. Section 5 performs two important robustness checks, concerning the role played by common shocks and the impact of monetary policies on yield spreads. Section 6 concludes.

2. The data

2.1 Construction of the corporate bonds yield series

The main issue with an analysis of bond market prices is that these markets are generally far less

[3] Bacchiocchi and Fanelli (2015) compare the IRFs for U.S. macroeconomic series of standard, recursive and non-recursive, heteroskedasticity-based identification schemes. However, their focus is neither on conventional vs. unconventional policies nor on the response by private debt markets to monetary shocks.

liquid and transparent than, for instance, equity markets (see Bessembinder and Maxwell, 2008). A large portion of the literature relies on indices of corporate bond yields (e.g., the classical indices produced by Moody's and Barclays) for research purposes (see, for example, Neal et al., 2000; Longstaff, 2010). One of the drawbacks of this practice, which may indeed affect the results of our analysis, is that these indices are typically constructed including, according to time-varying weights that reflect their relative market values, both callable and non-callable bonds. The callability feature (i.e., the option for the issuer to refunded a bond, at least partially, before the stated maturity) may have a significant impact on the behaviour of the bond yields: the value of the embedded short call option increases when the price of the bond rises, because when the interest rates fall, financing can be obtained at a lower cost. For this reason, we hand-construct corporate bond portfolio yield series, relying on transactions reported and collected by the Trade Reporting and Compliance Engine (TRACE), a system managed by the Financial Industry Regulatory Authority (FINRA). We merge the information on corporate bond trades with the details concerning the bond issues (such as their rating) retrieved from the Mergent Fixed Income Securities Database.[4]

The final step of the filtering process consists in classifying the observations according to maturity and rating: a bond is considered to be short-term (ST) if, at the time of the recorded trade, its remaining time to maturity is less than 5 years and long-term (LT) otherwise. Concerning the rating clusters, bonds are classified as investment grade (IG) if their rating is higher or equal than A- (in Standard & Poor's and Fitch scales) or A3 (Moody's scale) and non-investment grade (NG) otherwise. Next, we construct four series of weekly yields, one for each possible combination of the assigned cluster for rating and maturity, and obtain the following series of yields: investment grade short-term bonds (IGST), investment grade long-term bonds (IGLT), non-investment grade short-term bonds (NGST), and non-investment grade long-term bonds (NGLT). The weekly yield series for each portfolio are constructed by averaging the yields for all the bonds traded in each week and belonging to the portfolio.[5] The final results are four weekly (Friday-to-Friday) yield series for a sample October 1, 2004 - March 30, 2017.

2.2 Treasury bonds

The riskless U.S. yield curve is summarized by four series of constant maturity Treasury yields.

[4] We consider U.S. Corporate Debentures, Corporate Medium Term Notes, and U.S. Corporate MTN Zeros.
[5] For some trades, the yield is missing in the TRACE system: in that case we use the coupon rate, payment frequency, issue date, and remaining time to maturity to calculate the yield using standard formulas. We have also tried to build portfolios weighted by their outstanding amounts and found qualitatively similar results in terms of their means and standard deviations of the portfolio yields.

Constant maturity yields are interpolated by the U.S. Treasury from the daily yield curve.[6] In particular, we employ four weekly (Friday-to-Friday) time series of constant maturity yields: 1-month, 1-, 5-, and 10-year yields. Data are retrieved from the Federal Reserve Economic Data (FRED of Saint Louis) and cover the period October 1, 2004 - March 30, 2017.

3 Methodology

3.1 Baseline model and standard identification schemes

We assume the model has the following structural form

$$\boldsymbol{A}\boldsymbol{y}_t = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\boldsymbol{y}_t$ is the 8x1 vector of the eight endogenous variables, namely, the 1-month Treasury yield (1mT_t), the 1-year yield (1yT_t), the 5-year yield (5yT_t), the 10-year yield (10yT_t), the investment grade corporate bond short-term yield ($IGST_t$), the investment grade corporate bond long-term yield ($IGLT_t$), the non-investment grade corporate bond short-term yield ($NGST_t$), the and non-investment grade corporate bond long-term yield ($NGLT_t$). $\boldsymbol{B}_0$ captures the lagged effects of the endogenous variables y_t.[7] The 8x8 matrix $\mathbf{A}$ has diagonal elements equal to ones, while its off-diagonal elements capture the contemporaneous interactions across our endogenous variables. The vector $\boldsymbol{\varepsilon}_t$ contains the structural form white noise shocks, which are assumed to have zero mean and variance $\sigma^2_{\varepsilon,i}$ $\forall i$ = {1, ..., 8} and to be orthogonal to one another, both contemporaneously and across time:

$$\begin{aligned} E(\varepsilon_{i,t}, \varepsilon_{j,t}) = 0 \qquad & \forall i \neq j \\ E(\varepsilon_{i,t}, \varepsilon_{j,t'}) = 0 \qquad & \forall i \neq j, t \neq t'. \end{aligned} \tag{2}$$

Thus, the variance covariance matrix of the structural residuals is:

$$\boldsymbol{\Sigma}_\varepsilon = \begin{bmatrix} \sigma^2_{\varepsilon,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma^2_{\varepsilon,8} \end{bmatrix}. \tag{3}$$

The reduced form associated to the structural model is

$$\boldsymbol{y}_t = \boldsymbol{A}^{-1}\boldsymbol{c}_0 + \boldsymbol{A}^{-1}\boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_t = \boldsymbol{c}_1 + \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \boldsymbol{\eta}_t, \tag{4}$$

In which the residuals are related to the structural residuals by $\boldsymbol{\eta}_t = \boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_t$. It is well-known that the starting point for identification of the structural parameters is to estimate the reduced form model in (1) by OLS, obtaining estimates of $\boldsymbol{c}_1$, $\boldsymbol{B}_1$, and the covariance matrix of the reduced form

[6] That daily yield curve is based on the daily closing market bid yields on Treasury securities actively traded in the over-the-counter market.

[7] As it is customary, a VAR(p) with p > 1 can also be represented in companion form as a VAR(1) by simply expanding the vector of endogenous variables to include lags of $\boldsymbol{y}_t$ up to p -1. In the following we work with a VAR(1) representation while being aware that a higher-order VAR may be easily accommodated.

residuals (call them $\mathbf{\Omega}_\eta$); then, the structural coefficients ($\boldsymbol{c}_0$, $\boldsymbol{B}_0$, and the variances of structural shocks, the $\sigma^2_{\varepsilon,n}$ in $\mathbf{\Sigma}_\varepsilon$) should be retrieved from the reduced form estimates. Of course, if $\mathbf{A}$ were known, then this would be sufficient to recover the structural coefficients. In our case, because the covariance matrix of the reduced form residuals has 36 elements (i.e., 8 elements of the diagonal and 28 of covariances), we have only 36 equations for 64 unknowns (i.e., the 8 diagonal elements of the covariance matrix of the structural form residuals, given our assumption of zero correlation across structural shocks, plus the 56 off-diagonal elements of the matrix $\mathbf{A}$). Hence, there are more unknowns than equations, which means that a continuum of solutions exists.

Various methods of identification have been used in the literature: frequently the imposition of some (sign or exclusion) restrictions on some parameters, which are ideally derived from economic theory, have been employed, but such restrictions generally remain untestable. A commonly used method is the Cholesky decomposition which imposes that the matrix $\mathbf{A}$ is triangular, which in our application implies zero-restrictions on the contemporaneous effects among variables, to achieve exact identification. Unfortunately, the typical Cholesky restrictions, when applied to a model that contains asset prices, tend to be implausible and, as shown by Ehrmann et al. (2011), a standard Cholesky identification may fail to achieve the proper identification because of the strong asymmetries that it forces on the VAR system. As a result, in this paper we adopt an identification scheme based on the heteroscedasticity (in short, IH) that tends to characterize financial data.

3.2 Identification through heteroskedasticity

The theoretical derivation of the IH methodology and its application in the form of a GMM estimation methodology, have been developed in Rigobon (2003). The methodology is useful in any situation in which it is difficult to impose credible exclusion restrictions, like in the one at hand. The precise form of heteroskedasticity is not crucial in that framework. The key idea is that breaks/regimes in the reduced-form error covariance matrix can be associated with changes in the on-impact response of the variables to the shocks which in turn reflect in instabilities in the identified impulse response functions (IRFs) across volatility regimes. In our case, we shall assume a SVAR model with $S > 1$regimes in the covariance matrix of the structural form.[8] Such regimes help because they imply that each additional heteroskedastic regime adds more equations than unknowns in the system (in each regime we can estimate a new reduced form covariance matrix, each providing 36 equations, while there will be just 8 additional element to be estimated) and this feature leads to the solution of the problem of identification. Because the

[8] As shown in Rigobon (2003), the estimates of the conditional mean coefficients are consistent, regardless of how the heteroskedasticity is modelled, provided the number of regimes has been correctly specified.

lack-of identification can be pinned down in the need for 28 additional restrictions, but each regime provides 36 of them, clearly $S = 2$ is sufficient to exactly identify our VAR model.

This can be seen from the fact that when there are two regimes in the variances of the structural shocks, in practice, the sample can be split in two subsamples, one presenting high volatility and the other with low volatility. Assuming that the structural parameters are stable across the two regimes, we obtain

$$\boldsymbol{A}\boldsymbol{y}_t^s = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{y}_{t-1}^s + \boldsymbol{\varepsilon}_t^s \qquad s = 1,2, \tag{5}$$

where $Var[\boldsymbol{\varepsilon}_t^s] = \boldsymbol{\Sigma}_\varepsilon^s$, $\boldsymbol{\Sigma}_\varepsilon^1 \neq \boldsymbol{\Sigma}_\varepsilon^2$ with the covariance matrices of the reduced form shocks given by $\boldsymbol{\Omega}_\eta^1 \neq \boldsymbol{\Omega}_\eta^2$**.** In this new system of equations the unknowns are the $(N^2 - N) = 56$ elements of **A**, the $N = 8$ elements of $\boldsymbol{\Sigma}_\varepsilon^1$, and the $N = 8$ elements of $\boldsymbol{\Sigma}_\varepsilon^2$: overall there are 72 unknowns. Given the assumptions stated above, we can estimate a reduced form covariance matrix for each subsample: each covariance matrix provides $N + (N^2-N)/2 = 36$ elements. With two regimes, they are exactly 72 in total and the problem of identification is solved.[9]

We implement a recursive, pragmatic definition of regimes starting from the residuals of the estimated reduced-form VAR model and computing time-varying, rolling-window variances over 12-week samples for each variable: we identify a shift in regime every time the relative variances of one or several endogenous variables exceed their average value plus one standard deviation by at least a third of their standard deviation for a minimum of 24 weekly observations. We can identify 21 regimes in total, but restrict the analysis to the three "synchronized" regimes, i.e., those where at least one of the eight yield series exhibits an elevated conditional volatility, whereas all others do not show a conditional standard deviation that is abnormally low, plus a regime where all the interest rates series are in their "tranquil" zone. Using this procedure we achieve the identification of three separate regimes, both in the baseline cases and when exogenous shocks (see Section 4.2.1) are considered.

There is one additional necessary condition to achieve identification, besides the existence of heteroskedasticity, i.e., that in spite of the time-varying variances, the structural shocks remain uncorrelated. This assumption because crucial it implies that each additional heteroskedastic regime adds more equations than unknowns in the system and this feature leads

[9] When the data exhibit S heteroskedasticity regimes, the variances of the structural shocks in regime s are given by $\boldsymbol{\Sigma}_\varepsilon^s$ and the covariance matrix of the reduced form shocks is $\boldsymbol{\Omega}_\eta^s$. This latter can be estimated, providing $N + (N^2-N)/2 = 36$ additional equations, but only N additional unknowns, in each regime. For S regimes, the system that has $S[N + (N^2-N)/2]$ equations (one covariance matrix per regime) and $N^2 - N + SN$ unknowns (N structural variances for each regime, plus the parameters of **A**). A solution is guaranteed for $S[N + (N^2-N)/2] \geq N^2 - N + SN$, which is satisfied for $S \geq 2$. In particular, the system is exactly identified in presence of two regimes. Otherwise, the system has more equations than unknowns and those additional equations can be thought as testable over-identifying restrictions.

to the solution of the problem of identification.[10] As a matter of fact, in our application the identification problem is solved in the presence of at least two heteroskedasticity regimes: the system is identified by the heteroskedasticity existing in the data but still, this is only true up to a rotation of the matrix **A**.[11] Since all such rotations of the matrix allow us to solve the system of equations that would recover the structural conditional mean parameters from the reduced-form estimates, the sign restrictions we discuss below have the objective to ensure that we pick an economically meaningful rotation, i.e., the one which gives the best chances to correctly represent the underlying economic relationships (see Herwartz and Plodt, 2016, for details). Obviously, since the minimum number of regimes needed in order to exactly identify the structural form is exceeded by the three-state, empirical characterization of our data, the existence of one additional regime will lead to over-identification and thus to restrictions that are testable.

Specifically, the sign restrictions considered in our baseline model are as follows: since the Treasury term structure is upward sloping (a feature that will be confirmed on average also by our data, see Section 5), we assume that an increase in the yield of short term Treasuries has a positive effect on all other bonds with longer maturities, both Treasuries and corporate, which is generally consistent with the expectations hypothesis of the yield curve. Formally, given that in our case $\boldsymbol{y}_t \equiv [1mT_t \;\; 1yT_t \; 5yT_t \; 10yT_t \; IGST_t \; IGLT_t \; NGST_t \; NGLT_t]'$ and

$$\boldsymbol{A} \equiv \begin{bmatrix} 1 & \tau_{12} & \tau_{13} & \tau_{14} & \alpha_{15} & \alpha_{16} & \alpha_{17} & \alpha_{18} \\ \tau_{21} & 1 & \tau_{23} & \tau_{24} & \alpha_{25} & \alpha_{26} & \alpha_{27} & \alpha_{28} \\ \tau_{31} & \tau_{32} & 1 & \tau_{34} & \alpha_{35} & \alpha_{36} & \alpha_{37} & \alpha_{38} \\ \tau_{41} & \tau_{42} & \tau_{43} & 1 & \alpha_{45} & \alpha_{46} & \alpha_{47} & \alpha_{48} \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & 1 & \rho_{56} & \rho_{57} & \rho_{58} \\ \alpha_{61} & \alpha_{62} & \alpha_{63} & \alpha_{64} & \rho_{65} & 1 & \rho_{67} & \rho_{68} \\ \alpha_{71} & \alpha_{72} & \alpha_{73} & \alpha_{74} & \rho_{75} & \rho_{76} & 1 & \rho_{78} \\ \alpha_{81} & \alpha_{82} & \alpha_{83} & \alpha_{84} & \rho_{85} & \rho_{86} & \rho_{87} & 1 \end{bmatrix} \tag{6}$$

so that the τ parameters indicate the spillovers across Treasury yields of different maturities, the ρ parameters the spillovers across corporate bond yields of different rating and maturity clusters, and the α parameters the spillovers across Treasury and corporate yields. Although we have experimented with alternative sets of restrictions (results are reported in an Appendix available upon request), ultimately, our baseline case of consists of imposing $\tau_{21} < 0$, $\tau_{31} < 0$, $\tau_{41} < 0$,

[10] Bacchiocchi and Fanelli (2015) show instead that identification may be achieved even allowing the VAR matrices to change across regimes as well. However, this requires imposing additional exclusion restrictions on **A**, which may be undesirable in our application, or—which is our case—that the number of regimes exceed the strict minimum to achieve identification, here $S = 2$.

[11] A rotation is the multiplication of the matrix **A** by another matrix that is full rank and has determinant equal to one. Since both the matrix **A** and its rotation solve the system, the problem of how to differentiate the two is solved in practice by imposing additional exclusion or sign restrictions to force upon the methodology the selection of a unique rotation.

$\tau_{32} < 0$, $\tau_{42} < 0$, and $\tau_{43} < 0$.[12] Because we believe that these causality sequence should apply both to the direct effects of shocks on short-term rates (as measured by the matrix $\mathbf{A}$) as well as the overall effects, including indirect spillovers (as measured by $\mathbf{A}^{-1}$), we impose the equivalent set of restrictions on $\mathbf{A}^{-1}$.[13]

3.2.1 *Common shocks and estimation methodology*

We also consider a way to support the assumption of orthogonality of the structural form residuals. Indeed, this assumption may not be fulfilled if those residuals are driven by one or more common shocks. Such common shocks are very likely when asset prices (here, interest rates) are considered, because markets are tightly interconnected, even contemporaneously. The explicit introduction of common shocks allows us to model the possible covariance among residuals and thus to safely assume the orthogonality of the structural residuals after adequate transformations. In presence of common shock $\boldsymbol{z}_t$, our model has the following structural and reduced forms:

$$\boldsymbol{A}y_t = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{D}_0\boldsymbol{z}_t + \boldsymbol{\varepsilon}_t \tag{7}$$

$$\boldsymbol{y}_t = \boldsymbol{A}^{-1}\boldsymbol{c}_0 + \boldsymbol{A}^{-1}\boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{A}^{-1}\boldsymbol{D}_0\boldsymbol{z}_t + \boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_t = \boldsymbol{c}_1 + \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \boldsymbol{D}_1\boldsymbol{z}_t + \boldsymbol{\eta}_t, \tag{8}$$

where $\boldsymbol{D}_0$ captures the effect of the exogenous common shock. It may also be plausible to consider the lagged effects of the common shock $\boldsymbol{z}_t$, which would deliver the following structural and reduced forms:

$$\boldsymbol{A}\boldsymbol{y}_t = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{D}_0\boldsymbol{z}_t + \boldsymbol{F}_0\boldsymbol{z}_{t-1} + \boldsymbol{\varepsilon}_t \tag{9}$$

$$\boldsymbol{y}_t = \boldsymbol{A}^{-1}\boldsymbol{c}_0 + \boldsymbol{A}^{-1}\boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{A}^{-1}\boldsymbol{D}_0\boldsymbol{z}_t + \boldsymbol{A}^{-1}\boldsymbol{F}_0\boldsymbol{z}_{t-1} + \boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_t = \boldsymbol{c}_1 + \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \boldsymbol{D}_1\boldsymbol{z}_t + \boldsymbol{F}_1\boldsymbol{z}_{t-1} + \boldsymbol{\eta}_t \tag{10}$$

where $\boldsymbol{F}_0$ captures the effect of the lagged exogenous common shock. We conduct a robustness check with respect to the assumption of orthogonality of the structural form residuals of our baseline model in Section 6.1, introducing a common shock $\boldsymbol{z}_t$, both in its contemporaneous and lagged specification. All the common shocks are assumed to have zero correlation among them and with the structural shocks. The variances of shocks are $\sigma^s_{z,k}$ and $\sigma^s_{\varepsilon,n}$ respectively:

$$E_t(\varepsilon_{i,t}, \varepsilon_{j,t}) = 0 \qquad \forall i \neq j, \quad i,j = 1, 2, \ldots, K$$

$$E(\varepsilon_{i,t}, \varepsilon_{j,t}) = 0 \qquad \forall i \neq j, \quad i,j = 1, 2, \ldots, K$$

$$E(z_{i,t}, \varepsilon_{j,t}) = 0 \qquad \forall i \neq j, \quad i = 1, 2, \ldots, K \qquad j = 1, 2, \ldots, N \tag{11}$$

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[12] The sign of the restrictions are negative but this is not inconsistent with standard economic meaning because the matrix $\mathbf{A}$ pre-multiplies the endogenous variables on the left-hand side of (1).

[13] The sign restrictions limit the space in which parameters have to be searched to minimize the moment restrictions. This influences the speed of convergence but does not affect precision unless the estimates are on the boundaries. As we will see later, very few of the coefficients are on the boundaries, suggesting that only a small set of the restrictions are binding.

In our case, we have N = 8 equations and K = 1 common shock, the number of equations is given by the covariance matrix in each regime, i.e., $S[N + (N^2–N)/2]$ in total, while the unknowns are the elements of matrix $\mathbf{A}$, i.e., $(N^2 - N)$, the elements of matrix $\mathbf{D}_0$, i.e., $K(N - 1)$, the variances of the common shocks in each state, i.e., KS, and the variances of the structural shocks in each regime, i.e., NS. In general (see Rigobon, 2003), the system is identified if and only if, the number of states satisfied $S[N + (N^2–N)/2] \geq N^2–N + K(N - 1) + SK + SN$ or

$$S \geq 2\,\frac{(N+K)(N-1)}{N^2-N-2K} \tag{12}$$

and if one additional regime in the covariance matrix adds more equations than unknowns, i.e., the number of common shocks satisfies $N^2 - N - 2K > 0$, then $K < (N^2 - N)/2$. In our case with $N = 8$ and $K = 1$, equation (12) is obviously satisfied. This means that with the introduction of one or two common shocks, the identification problem is exactly solved in the presence of three heteroskedastic regimes, but the ability to perform over-identifying tests disappears.

For the purposes of our analysis, it is reasonable to consider that the structural residuals of our model might be influenced by the prevailing general business conditions. For that reason, we employ the Aruoba-Diebold-Scotti business conditions index to measure common shocks.[14] The Aruoba-Diebold-Scotti business conditions index (ADS index) is aimed at tracking real business conditions: the average value of the ADS index is zero and it assumes larger (positive) values to indicate better-than-average conditions, or lower (negative) values, to signal worse-than-average conditions. Thus, the ADS index is suitable to obtain a measure of time-varying business cycle conditions. The ADS index is updated continuously as new data are released, which is at least once a week: we use the vintages available for our sample period (from October 1, 2004 to March 30, 2017) from the website of Federal Reserve Bank of Philadelphia.[15]

Once the number of regimes has been identified, we estimate the parameters of interest by minimizing the following minimum distance function

$$\min_{\boldsymbol{\theta}\in\mathbb{C}} \sum_{s=1}^{3}\left\{\boldsymbol{A}'\boldsymbol{\Sigma}_{\varepsilon}^{s}\boldsymbol{A} - \boldsymbol{\Omega}_{\eta}^{s}\right\}'\left\{\boldsymbol{A}'\boldsymbol{\Sigma}_{\varepsilon}^{s}\boldsymbol{A} - \boldsymbol{\Omega}_{\eta}^{s}\right\} \tag{13}$$

where $\mathbb{C}$ is the sub-space of values for $\boldsymbol{\theta}$ such that the sign constraints specified under equation (6) are satisfied, $\boldsymbol{\theta}$ collects the parameters to be estimated, $\boldsymbol{\theta} \equiv vec(\boldsymbol{A})'$, $\boldsymbol{\Sigma}_{\varepsilon}^{s}$ is the regime-specific diagonal matrix of variances of the structural shocks, and $\boldsymbol{\Omega}_{\eta}^{s}$ is the covariance matrix of the reduced-form residuals we estimated in each regime s = 1, 2, 3. The criterion function is replaced

[14] The ADS index is based on a number of observable economic indicators: weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP, see Aruoba et al. (2009).

[15] Concerning the revisions to the ADS index, Berge and Jordà (2011) argue that data revisions should affect indices much less than single series, and Chauvet and Piger (2008) find that business cycle turning points are robust to data revisions.

by $\{\boldsymbol{A}'\boldsymbol{\Sigma}_\varepsilon^s\boldsymbol{A} - \boldsymbol{D}_0{}'\boldsymbol{\Sigma}_z^s\boldsymbol{D}_0 - \boldsymbol{\Omega}_\eta^s\}'\{\boldsymbol{A}'\boldsymbol{\Sigma}_s\boldsymbol{A} - \boldsymbol{D}_0{}'\boldsymbol{\Sigma}_z^s\boldsymbol{D}_0 - \boldsymbol{\Omega}_\eta^s\}$ when there are common shocks, where $\boldsymbol{\Sigma}_z^s$ is the covariance matrix of the common shocks in regime s, which is assumed to be a diagonal matrix with elements $\sigma_{z,k}^s$. This is analogous to a GMM estimator (see Rigobon, 2003), the distribution of which is easily derived, at least asymptotically. Interestingly, the consistency of estimates is preserved even when the data contain *more* regimes than the ones specified, although consistency when the data contain less regimes may be more problematic. Identification requires the equations to be linearly independent, which is assured by the fact that the volatility of one of the observed variables is elevated, while the others are relatively stable. Because the model has over-identifying restrictions—we only need two regimes and we shall have 3—we can test the over-identifying restrictions in the usual way.

As we do not want inferences to rely on asymptotics, we block-bootstrap the p-values of our parameter estimates. For each of the heteroskedasticity regimes, we use the estimated regime-specific covariance matrices to create new data with the same covariance structure in each bootstrap replication. For each draw, we estimate the coefficients by minimizing the moments given the restrictions. We use 5,000 bootstrap replications.

3.3 Impulse response policy experiments

We follow the tradition in applied macroeconomics and use impulse response functions (henceforth, IRFs) to quantitatively track between h= 1 and h = 52 weeks (since inception of one or more shocks) and understand the effects of monetary shock of different types on corporate bond yields. However, when identification is supported by regimes that occur only in the covariance matrix of the structural residuals, because a unique matrix of the contemporaneous, structural effects (along with the dynamic VAR matrices, assumed to be constant over time) implies time-homogeneous IRFs (see Bacchiocchi and Fanelli, 2015).

It is possible to extend the concept of IRF to non-linear models by defining a generalized IRF (see, e.g., Koop et al., 1996), with reference to a regime-switching framework that also involves matrices of parameters the enter the conditional mean function of the SVAR. In our case, we assume that the conditional mean dynamic parameters ($\mathbf{B}_1$ and $\mathbf{D}_1$, where present) are in no way dependent on the variance regimes that simply enter in the identification of the SVAR. However, the residual covariance matrices $\boldsymbol{\Omega}_\eta^s$ s = 1, 2, 3 that enter the GMM problem in (13) depend on the regime and offer the opportunity to solve three distinct local problems,

$$\min_{\boldsymbol{\theta}_s \in \mathbb{C}} \{\boldsymbol{A}_s{}'\boldsymbol{\Sigma}_\varepsilon^s\boldsymbol{A}_s - \boldsymbol{\Omega}_\eta^s\}'\{\boldsymbol{A}_s{}'\boldsymbol{\Sigma}_\varepsilon^s\boldsymbol{A}_s - \boldsymbol{\Omega}_\eta^s\}, \tag{14}$$

in which also the matrices of the contemporaneous cross-variable effects have been made regime-dependent. As shown by Bacchiocchi and Fanelli (2015), in this case the estimation procedure simplifies to (14), which is a special case of non-linear least squares estimation.

An h-step-ahead IRF is then defined as

$$IR_{\Delta\boldsymbol{\varepsilon}}(h) = E[\boldsymbol{y}_{t+h}|\boldsymbol{y}_t(\boldsymbol{\varepsilon}')] - E[\boldsymbol{y}_{t+h}|\boldsymbol{y}_t(\varepsilon)]\,, \quad (15)$$

where the sample path $\boldsymbol{y}_t(\boldsymbol{\varepsilon}')$ is equal to the sample path $\boldsymbol{y}_t(\boldsymbol{\varepsilon})$ with the exception of the initial value of $\boldsymbol{y}_t$, which has been perturbed by a shock $\Delta\boldsymbol{\varepsilon}$ (see Potter, 2000). In practice, an IRF measures the difference between the conditional expectation of $\boldsymbol{y}_{t+n}$ at time t in case $\boldsymbol{y}_t$ has been subject to a shock and the conditional expectations of $\boldsymbol{y}_{t+n}$ at time t in case $\boldsymbol{y}_t$ has not been shocked. This definition can be generalized to fit a regime switching framework as:

$$IR_{\Delta\boldsymbol{\varepsilon}}(h,s) = E\left[\boldsymbol{y}_{t+h}\middle|S_{t,}\boldsymbol{\varepsilon}_t + \Delta\boldsymbol{\varepsilon}; \boldsymbol{y}_{t-1}\right] - E\left[\boldsymbol{y}_{t+h}\middle|S_{t,}\boldsymbol{\varepsilon}_t; \boldsymbol{y}_{t-1}\right]. \quad (16)$$

In a regime-switching framework, an h-step-ahead IRF depends on the state S_t prevailing at time t when the shock occurs because it affects the estimated matrix of contemporaneous effects, $\boldsymbol{A}_S$. Notably, because we analyze models with regimes in which the VAR matrix is not regime-dependent, we only need information about the state prevailing at the time the shock occurs. Even though more complex approaches are possible (Monte Carlo techniques to simulate the ergodic distribution of regimes, or assuming equal probabilities across regimes), in this paper we assume that the regime prevailing when the shock occurs is known, which is also consistent with Sections 3.1 and 3.2.

Because IRFs are computed using estimated coefficients, they clearly also reflect estimation error. Accordingly, we construct confidence intervals for the IRFs using bootstrapping techniques (see Killian, 1998). To implement the bootstrap method, each equation is estimated by OLS and a series $\{\boldsymbol{\eta}_t\}$ of T errors (T is the sample size) is constructed by random sampling with replacement from the estimated residuals. The series $\{\boldsymbol{\eta}_t\}$ and the estimated coefficients are then used to construct $\{\boldsymbol{y}_t^1\}$. Finally, the coefficients used to generate $\{\boldsymbol{y}_t^1\}$ are discarded and new coefficients are estimated from $\{\boldsymbol{y}_t^1\}$ following the methods in this Section, obtaining a new time series of residuals $\{\boldsymbol{\eta}_t^1\}$. The re-sampled impulse response function indexed as 1 is computed from the new estimated coefficients. At this point, starting from the $\{\boldsymbol{\eta}_t^1\}$, the algorithm is re-started to construct $\{\boldsymbol{y}_t^2\}$ to estimate new coefficients and obtain both new residuals $\{\boldsymbol{\eta}_t^2\}$ and a re-sampled impulse response function indexed as 2. This process is iterated a total of M times. When this process is repeated for a sufficiently large number of times, the resulting set of M simulated impulse response functions can be used to construct the confidence intervals. For example, a 95% confidence interval is the one that excludes the highest and the lowest 2.5% of the bootstrapped, re-sampled IRFs. In the paper we set M = 5,000. An impulse response function is considered statistically significant if zero is not included in the bootstrapped confidence interval.

In order to simulate the three monetary policies we are interested in, we consider their effects on Treasury rates (as suggested by Bernanke and Blinder, 1992). This approach relies on two main assumptions: (i) in the conventional monetary policy case, Fed funds rate and 1-month Treasury yield tend to co-move; (ii) in unconventional monetary policies case, QE, and MEP, are at least able to lower Treasury yields. Whether or not such an impulse may be transmitted over to corporate bond yields represents instead the main research question of our analysis. We follow this approach for two reasons: first, the traditional approach of measuring conventional monetary expansion by changes in monetary aggregates fails to recognize that the rate of growth of monetary aggregates depends also on the trend of growth of the currency component of the money supply (see Bernanke and Mihov, 1998); second, in the case of the MEP, the policy does not imply the creation of monetary base but instead it induces a change in the relative supply of long- and short-term Treasuries so that it would be impractical to simulate such policies with an approach based on shocks to monetary aggregates.

The premise of this paper is that both conventional and unconventional policy shocks can be approximated as changes in nominal Treasury yields. While in the case of Fed fund rate-driven policies this represents a persuasive choice, in the case of QE and the MEP, Treasury yields are just intermediate targets for monetary policy and we may wonder whether it is realistic to assume that a one-time unconventional policy shock may be causing a large effect on Treasury rates. There is a growing literature trying to pin down the quantitative impact of Fed actions on the Treasury yields with varying findings but these vary between approximately 5 bps (as in Gagnon et al., 2011) and 70 bps (as in D'Amico and King, 2013) per week per 100 billion of QE intervention, and between 3 and 15 bps per 100 billion of MEP intervention (see Hamilton and Wu, 2010; Swanson, 2011). Because the average of LSAP 1–3 may be quantified in approximately US450$ billion, assuming the policy had not been anticipated, this corresponds to a shock in the range 22-315 bps; similarly, because the MEP consisted of a plan to purchase US$400 billion of Treasury securities with remaining maturities of six years to 30 years and to sell an equal amount of Treasury securities with remaining maturities of three years or less, this maps, assuming the change in policy had been unexpected, in a shock between 12 and 60 bps.

In practice, using the 1-month Treasury yield to represent short-term Treasury rates and the 10-year Treasury yield to represent long-term rates, we simulate a conventional monetary expansion, which implies a shock to the short-end of the yield curve, through a negative shock to the 1-month Treasury yield; we represent QE inception, i.e., the purchase of long-term securities, through a negative shock to the 10-year Treasury yield; and we simulated MEP, i.e., the sale of short-term Treasury notes and the contemporaneous purchase of longer term ones, through a negative shock to the 10-year Treasury yield accompanied by a simultaneous positive shock to the 1-month Treasury yield. As in most of the literature, the shock considered is equal to one standard deviation.[16]

4 Empirical results

4.1 Regime definition

We use the reduced form residuals from an estimated VAR(1) in order to define the heteroskedastic regimes.[17] First, we compute rolling window estimates of the variance of each residual series: each window has a length of 12 weekly observations. We identify a regime shift every time the relative variances of at least one residual series exceeds its historical sample average (up to that time t) value plus one (historical, sample, up to time t) standard deviation by at least a third of the standard deviation, for at least a minimum period of 24 weekly observations.[18] This procedure leads to define three regimes. Because the consistency of the GMM estimator holds when the number of regimes in the data is under-identified vs. the true, but unknown data generating process, a parsimonious selection of S =3 seems appropriate.[19]

Figure 1 reports evidence on the nature of the three heteroskedasticity regimes. Regime 1 is the regime recurring more often: it accounts for about 65% of observations in the sample. In this regime the estimated variances of structural shocks (see Table 1) are lower than in the other regimes (with the exception of 10-year Treasury yield shocks, which display a lower variance in Regime 2). Although the regime-specific means are in no way used in their definition, we also note that the residuals of both corporate bonds and Treasuries in this regime have means that are lower than those in the overall sample. Thus, regime 1 can be considered a frequently occurring and tranquil state characterized by low expected yields for all types of bonds.

Regime 2 is the least frequent regime: it accounts for less than 6% of observations in our sample and appears to have occurred in the 2006-2007 period (see Figure 1). In this regime, residual variances are structurally higher than in regime 1 (excluding the cases of NIGLT bonds

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[16] Note that the structure of the IRFs is not altered by adding (simultaneous and lagged) common shocks, as the latter are not perturbed by the policy impulse(s) and thus they cancel out as it is the well-known case of the constant term.

[17] To select the proper order of the VAR model, we follow Lütkepohl (1985) who, using simulations, has found that the Bayesian Information Criterion (BIC) tends to perform best among information criteria when the task is to select the VAR order When p ranges between 0 and 10, we select a VAR(1) model. The models turns out to be stable and hence covariance stationary. The OLS estimates of the model are reported in an Appendix available upon request from the Authors.

[18] This regime specification turns out to be robust both to other combinations of rolling window selections and threshold values for relative exceedance and to the introduction of common shocks in the model.

[19] We formally test the occurrence of the regimes in the reduced-form variances through a standard LR Chow-type test. We focus on the null hypothesis that the VAR reduced-form residual variances are constant across the three regimes, $\boldsymbol{\Sigma}_\varepsilon^1 = \boldsymbol{\Sigma}_\varepsilon^2 = \boldsymbol{\Sigma}_\varepsilon^3$ for a total of 72 restrictions. The null hypothesis of stable parameters is clearly rejected. The LR statistic is equal to184.58 and has a p-value of 0.000 (from the $\chi^2(72)$ distribution). Also the LR Chow-type test for the null hypotheses $\boldsymbol{\Sigma}_\varepsilon^1 = \boldsymbol{\Sigma}_\varepsilon^2$, $\boldsymbol{\Sigma}_\varepsilon^2 = \boldsymbol{\Sigma}_\varepsilon^3$, and $\boldsymbol{\Sigma}_\varepsilon^1 = \boldsymbol{\Sigma}_\varepsilon^3$ (i.e., of only two regimes instead of three) are rejected with p-values between 0.000 and 0.011.

and 10-years Treasuries) but lower than in regime 3. Also the means are higher in this regime vs. regime 1 for all corporate bond and Treasuries series, whereas the standard deviations of the series are *lower*. The simultaneous occurrence of higher residual variances with lower variances of the series indicates that the R-squares implied by our VAR(1) filter structurally decline in this regime. Thus, we consider regime 2 as a transient state, essentially preceding the crisis state, in which bond markets were characterized by high yields and low volatilities.

Regime 3 is characterized by the highest variances of residuals (see Table 1), with the exception of investment grade long-term bonds. In particular, the variance of the residuals of the series of NIG corporate bond yields skyrocket. This regime accounts for about 30% of the observations in our sample, including the credit crunch phase following the 2008 crisis and 2010-2011, when short-term Treasuries reached the zero lower bound and the warning of a U.S. debt crisis ceiling dominated the news. The LSAPs of March 2009, the MEP and LSAP3 are all captured by this regime. Focusing on the means and standard deviations in Tables 3 and 4, the average yields of corporate bonds are higher than in the other two regimes (excluding the IGST series, which has higher mean yield in regime 2), while the means of the yields of Treasuries are lower vs. regime 2. Regime-specific standard deviations are the highest in this regime for corporate bonds (in particular, for NIG corporate paper), while they are similar to regime 1 as far as Treasuries are concerned. Thus, regime 3 is a crisis state, if we consider that during markets crashes, investors tend to move towards safer assets (i.e., Treasuries and to some extent, IGST bonds), lowering their yields, while causing the yields to climb for high-risk bonds (i.e., non-investment grade corporates).

4.2 Estimation and identification through heteroskedasticity

The estimated matrix **A** is reported in Table 2: on the basis of the bootstrapped p-values of the t-test applied to the individual coefficients reported in parenthesis, the entire matrix is highly statistically significant. The coefficients measuring contemporaneous effects among corporate bonds are particularly large: the positive spillovers across corporate bond yields of shorter maturities on the longer term ones in the same rating cluster are the strongest effects we report.[20]

The highest spillover effects involving Treasuries are instead those from the shortest maturities to longer term bonds, which is an implicit feature of the upward sloping term structure

[20] As discussed in the main text, the standard, BIC-based steps for the specification of the VAR models in each regime suggests the inclusion of one lag. The included dynamics, however, turned out to be insufficient for cleaning the residuals from departures from normality, especially excess of kurtosis. Yet, increasing the number of lags hardly helped to solve the problem. This justifies our use of GMM as an estimation method, while all ensuing inferences should be referred to as 'quasi'-LR tests). As expected, the residuals show strong signals of heteroskedasticity, which justifies the identification through heteroskedasticity strategy pursued in the paper. Detailed results are available upon request.

of Treasuries under the Expectations Hypothesis. Spillovers across Treasury and corporate bond yields are generally weaker, even though all of them are precisely estimated. Exceptions are represented by the negative contemporaneous effect among short-term bonds, in particular the 1-month T-bill rates and the yields of IGST. This empirical result appears to be consistent with the preferred-habitat theory, since bonds in the same maturity segment should be considered as substitutes in terms of investment choices for a specific preferred-habitat investor.[21]

Under S = 3 regimes, Section 3 shows that a heteroskedasticity-based identification strategy leads, when N = 8 and p = 1, to 28 over-identifying restrictions. The model fails to be rejected from a formal (quasi) LR test: under the null hypothesis consisting of the 28 restrictions, the LR statistic is equal to 35.04 and yields a p-value of 0.169 (under the $\chi^2(28)$ distribution).

As a last step, we also test whether the dynamics of the VAR are also time-varying through a test of H$_0$: $\boldsymbol{A}_1 = \boldsymbol{A}_2 = \boldsymbol{A}_3$ but $\boldsymbol{\Sigma}_\varepsilon^1 \neq \boldsymbol{\Sigma}_\varepsilon^2 \neq \boldsymbol{\Sigma}_\varepsilon^3$ vs. the alternative that $\boldsymbol{A}_1 \neq \boldsymbol{A}_2 \neq \boldsymbol{A}_3$ and $\boldsymbol{\Sigma}_\varepsilon^1 \neq \boldsymbol{\Sigma}_\varepsilon^2 \neq \boldsymbol{\Sigma}_\varepsilon^3$ (and implicitly the regimes defined by heteroskedasticity are aligned with those for the conditional mean function). In both cases, the sign restrictions that follows equation (6) and that uniquely define a rotation of the $\boldsymbol{A}_s$ matrices have been imposed. In this case, the (quasi-)LR test becomes equals 144.49 and allows to reject the null with a p−value =0.021 (taken from a $\chi^2(112)$ distribution). We thus find formal support that the three breaks involve both the conditional mean and conditional covariance matrix of the VAR model.

4.3 Effects of a conventional monetary expansion

We now turn now to the computation of the IRFs for the three types of shocks which represents a conventional monetary expansion, the QE program, and the MEP, respectively. Figures 2-4 show the IRFs of corporate bonds of all rating and maturity clusters in each one of the three regimes and over a response interval of 52 week along with bootstrapped 95% confidence intervals. The common interpretation applies: for given h between 1 and 52 weeks, an IRF is not statistically significant at 5% size if zero is included in the 95% confidence interval, since we cannot reject the null hypothesis that the response is equal to zero at the chosen test size.

Starting with the analysis of the implications for corporate yields of a conventional expansionary monetary policy, simulated as a negative one standard deviation shock in the 1-month Treasury yield (approximately equal to 41 bps, but here we need to recall that in spite of

[21] The preferred-habitat theory has been firstly presented by Culbertson (1957) and recently formalized by Vayanos and Vila (2009). While the traditional expectation hypothesis states that the presence of risk-neutral agents implies that the term structure is determined only by current and expected future short rates, the preferred-habitat theory states that markets are segmented and the relative supply of assets influences their yields for each specific maturity. In this framework, preferred-habitat investors have a strong preference for a specific maturity segment and demand only bonds that correspond to their maturity habitat.

their high correlations, 1-month rates are an imperfect proxy for shocks to the Fed funds rate), we report that—in contrast with the expected effects of an expansionary monetary policy and with its objectives from the point of view of policy-makers—our analysis of corporate yields responses shows that this policy leads to a generalized *increase*, rather than a decrease, of corporate rates.[22] In particular, this effect is stronger for NIG bonds, it leads to a maximum impact within the first month from the implementation of the policy, and the result appears to hold not only in the crisis state (where it is strongest), but mildly so also in the tranquil and in the transient regimes. In terms of persistence, any statistically significant effects declines rapidly, reaching zero after the firth to sixth month after the occurrence of the shock.

In the crisis regime 3, this perverse effect is stronger in terms of magnitude in all cases, similarly to Dahlhaus (2017); the most significant increases in yields are those recorded for short-term bonds: in the periods subsequent to the implementation of the policy, non-investment grade bonds are subject to an increase in a range of 60-80 bps, whereas the maximum impact on IG yields is around 22 bps, recorded in the second week after the shock occurs. As far as long-term yields are concerned, the estimated effects are significant only in the fifth week after the policy implementation for investment grade bonds (a positive increase of 13 bps is registered) while for NIG corporate yields, a peak increase by 74 bps appears after 4 weeks.

In both regimes 1 and 2, a conventional, expansionary policy has a positive and significant effect on IGST yields, inducing an increase in the rate of those assets of the order of 1 and 5 bps, respectively. Investment grade long-term bonds are not characterized by a significant increase in their yields. Non-investment grade yields in both maturity clusters are subject to a statistically significant increase in regime 1 and 2 in the order of 4 and 15 bps, respectively.

Our findings are consistent with those in Guidolin et al. (2017), who found that the corporate yield effects of conventional monetary policy often carry the wrong sign given the desiderata of policy-makers. These results should be carefully assessed for their implications on policy management, for instance in terms of the signals to the fixed income market about future inflation and growth implied by an expansionary monetary policy. In fact, an expansionary policy is generally regarded as an indicator of future inflation, because it implies an increase in the monetary base and more generally represent a stimulus to aggregate demand. In addition, in times of crisis, a Fed funds rate reduction that is quickly transmitted to the rate of 1-month T-bills, is likely to signal to the market a concern by the Fed about the general macroeconomic state, and may generate negative expectations about the future of the economy. Coherently with the findings of Bernanke and Mihov (1998), our results demonstrate that the response of corporate

[22] Even in normal times, the Fed might be using non-borrowed reserves in addition to short rate manipulation to perform conventional monetary policy. We abstract from this aspect in our analysis.

yields to an expansionary monetary shock may depend on the economic regime prevailing at time when the shock occurs, being it stronger in the case of crisis state. It also is worth noting that in the third regime, policy rates were constrained by the zero lower bound, so that a conventional policy can hardly be expected to be effective when measured by a negative shock to short-term rates. Moreover, Kontonikas et al. (2013) have reported that, during the 2007-2009 financial crisis which is mostly captured by our regime 3, the elevated uncertainty led to an increase in riskier (i.e., non-investment grade) yields, while policy rates were being sharply cut, which is a result in line with the positive and significant IRF estimated in particular for NIG corporate bonds.

4.4 Effects of quantitative easing

We have analysed the effects on corporate yields of the QE program, simulated as a one standard deviation negative shock to the 10-year Treasury yield, which is approximately 61 bps on impact; this falls towards the lower end of the 22-315 bps range that has been reported with reference to LSAP1-3. The responses to QE by corporate yields are shown in Figure 3 and are remarkably different across maturities. Long-term yields significantly decline, while short-term yields mark a significant increase: in particular, the increase is registered after about 6 months from the implementation of the policy in the case of IG bonds and in the period immediately after the shock occurrence in the case of NIG bonds. In general, responses to QE-type policies are more persistent vs. the ones obtained for the case of a conventional monetary expansion. For that reason, we also estimate the IRFs over a horizon exceeding the 52-weeks reported in Figure 3 and find that any effects decline in their magnitude and stop being statistically significant approximately after 70 weeks from the implementation of a QE-type shock.

The effect on IGLT yields is a statistically significant decrease in all regimes considered: of 14 bps in the crisis state and of about 6 bps in both regimes 1 and 2. The same holds for non-investment grade corporate bonds of the same maturity (excluding the first period when the effects are not statistically significant). In that case, the maximum decline in the crisis state is of 45 bps, whereas in the tranquil regime yield declines by 20 bps and in the transitory regime by 16 bps. All this effects are generally precisely estimated and economically sizeable. The response of NIGST yields in all regimes is first a significant increase (in the order of 10 bps), and then a persistent decrease, lasting about 6 months, up to 8 bps, 6 bps, and 18 bps in the tranquil, transitory, and crisis states, respectively. In the case of IGST corporates, QE seems to produce insignificant effects neither in regime 1, 2 or 3, for the first 10 months approximately. Then, an increase of the yield is recorded in all the regimes (in particular in the crisis state). Nevertheless, the magnitude of this effect slowly decreases after period 52 and stops being precisely estimated.

Excluding the case of IGST bonds, these effects found are consistent with the policy objective of reducing the borrowing costs for firms. Noticeably, the strongest effects of QE are obtained in the regime of crisis, which is precisely when the policy is most likely to be implemented/needed, even though the objective of reducing the cost of debt faced on average by firms may also be achieved (probably, at the cost of having to scale up the size of the QE operations) also in regimes 1 and 2.

Compared to the IRF results in Guidolin et al. (2017), our effects are larger in magnitude for IGLT bonds and smaller for NIG bonds. This difference might be caused by the simpler—possibly problematic—identification strategy applied by Guidolin et al., i.e., a Cholesky triangularization by which the variable ordering plays a crucial role and investment grade bonds are causally prior to non-investment grade ones, so that it is exactly IG corporate papers that appears to be most influenced by shocks to other variables. Although this may be consistent with a preferred habitat hypothesis for interest rates, the lack of robustness of their conclusions to the identification strategy should alert policymakers of the fact that QE strategies may have effects exactly those where these are most needed in times of crisis, to lower the cost of capital of firms of less-than perfectly credit quality.[23] More generally, the literature that has investigated the effects that QE has produced on risky yields of assets different from those purchased directly by the Fed (e.g., Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2010) did report that QE was effective only in reducing their yields. However, our analysis also reveals that the effects of QE are statistically significant and carry the desirable sign even in regimes 1-2, different from the crisis one, indicating that this policy should steadily enter (as it seems to have, see Farmer and Zabczyk, 2016) the toolkit available to policymakers, regardless of the GFC-related events that did lead to promote these policies in late 2008.

4.5 Effects of the maturity extension program (Operation "Twist")

Figure 4 reports the IRFs concerning corporate yields when the shock mimics the effects of the MEP, that we simulate as a one-standard deviation negative shock to the 10-year Treasury yield accompanied by a positive one-standard deviation shock to the 1-month Treasury yield (see estimates reported above). In general, the effects generated by MEP are precisely estimated and carry a sign that agrees with the direction desired by monetary authorities, as it triggers a reduction in yields in every regime, in particular in the crisis one. However, the yield responses turn less persistent than in the case of QE in Figure 3. For instance, in the case of the IGST yield, the response lasts a shorter period and the rate decline is of about 2 bps, 4 bps, and 22 bps in the tranquil, transitory, and the crisis regimes, respectively. Declines of a similar magnitude are

[23] ALthough Guidolin et al. (2017) perform robustness checks on the Cholesky ordering and report generalized IRFs, the tendency of the response of high-grade to exceed that of low-grade rates is pervasive.

estimated for IG long-term yields, although their responses are more persistent. The effects of the MEP on NIG yields are significant and larger than those of any other policy: short-term NIG yields decline by up to 70 bps in the crisis state, 9 bps in tranquil regime, and 15 bps in transitory regime; in the case of long-term yields, significant effects appear after a few periods from occurrence of the shock and the overall decline totalled reaches about 22 bps in the tranquil regime, 28 bps in transitory state, and 107 bps in the crisis state. These are hefty policy effects.

Differently from the case of QE in Figure 3, the IRFs to MPE shocks show the expected signs and are significant in a rather homogeneous fashion. The effects are particularly relevant in a policy perspective in the case of all short-term rates. This can be explained by the peculiar nature of the MEP, which is a policy aiming at reducing the slope of the Treasury yield curve without increasing the monetary base (see Hamilton and Wu, 2010), thus without inducing expectations of an increase in inflation. In fact the results in Figure 4 contribute to shed further light on the findings in Figure 3 concerning the QE program, as this does imply the creation of monetary base and a likely impact on inflation expectations (see, e.g., Bernanke and Mihov, 1998). Moreover, in regime 3, these results appear to be qualitatively in line with—but of stronger magnitude, which is of course of practical relevance and in accordance to Mishkin's (2009) conjecture that monetary policy may be more effective just in times of crisis—those in Gilchrist et al. (2015) and Guidolin et al. (2017); however, the IRFs in Figure also reveal non-negligible and precisely estimated effects in regimes 1 and 2, which is not the case in Guidolin et al.'s paper, where however an arguably weaker (because arbitrary) identification scheme had been applied.

Our finding that that the MEP may be more effective than QE is partly surprising, although earlier papers had assessed MEP to be a remarkably effective strategy (e.g., see Hamilton and Wu, 2010) through a duration risk channel, to be contrasted to a simpler monetary base one. However, we should recall that our empirical assessment is only focussed on the cost of private debt and assumes effects on Treasury rates that are data-driven. It would then be tempting to jump to the conclusion that in the case of QE, the resulting expansion of the monetary base may have acted to significantly offset its effectiveness of QE so that the FED might have achieved much better results if it had sterilised all of their purchases. Yet, we need to remember that, unless special and possibly undesirable arrangements were established with the Treasury, the practical size of MEP has as its natural bound the initial amount of bills and short-term notes in the FED's portfolio, which makes of MEP a useful but not all-purpose weapon in a central bank's arsenal.

5 Discussion and robustness checks

5.1 The effects of common shocks

The introduction of common shocks in the model allows us to relax the assumption of orthogonality of the structural residuals, as explained in Section 4. We start by introducing one common shock and estimating the VAR(1) model as in (8), when the common shock concerns the ADS business conditions index. By applying the same methodology as in Section 5 (also as far the selection of p = 1), we find that the regime definition based on the dynamic, rolling window residual variances leads to the same number and characterization of the regimes as in Section 5 and Table 1. In fact, a comparison of Tables 3 and 1 reveals negligible differences, of 10% at most in the largest estimated residual variances.

Coefficients of the, covariance stationary (as shown by the characteristic roots) estimated VAR(1) are reported in an Appendix. In any event, the results are quite similar to those in the baseline model, in terms of significance, sign, and magnitude of the estimated conditional mean coefficients. Interestingly, more than a half of the coefficients relating one lag of the ADS index are significant and, at least in general, a high level of the business cycle index forecasts higher Treasury yields (the only exception occurs with reference to the 10-year Treasury, for which the estimated coefficient fails to be significant) but lower corporate yields. The direction of these effects might be explained thinking that a higher ADS index indicates above average economic conditions, which may induce investors in moving from safer investments (such as Treasuries, whose price declines and yields climb up) to investments in riskier assets (such as corporate bonds, especially of NIG type) which therefore display lower, subsequent rates. In this perspective, also the weaker effects estimates for 10-year Treasury rates are sensible, as long-term government bonds at least imply high duration risk.

The GMM-estimated matrix **A** obtained from identification through heteroskedasticity methodology for this model specification is shown in Table 4, panel A. Interestingly, also the estimated matrix of contemporaneous effects is hardly affected by the introduction of common shocks, so that Table 4 resembles Table 2. The key exception involves NIGST yields, which are now positively influenced by Treasury yields of all maturities. Another substantial difference is that shorter term Treasuries (1-month and 1-year) are negatively influenced by the yields of NIGST bonds and investment grade long-term bonds, respectively, albeit the magnitude of the effect is relatively small (and yet precisely estimated).

Given the estimated parameters presented above, we compute the IRFs for the three policies studied in Section 5 and report the results in Figure 5. The effects produced by a conventional monetary expansion are the same for yields of all rating-maturity clusters and regimes, in terms of sign, magnitude, significance, and persistence: in regimes 1 and 2 the effects are modest and usually not statistically significant; in regime 3, exactly when policies were most needed, the responses turn perverse (although there is also considerable imprecision, also because short-term rates were hardly actually used to affect interest rates in the periods that are best characterized as regime 3) in the sense that an expansionary policy would push corporate bond yields higher and hence discourage investments and production. In the case of the IRFs that refer to the QE programs, the responses have the expected signs and tend to be precisely estimated in regime 3, especially for long-term corporate bonds, both NIG and IG and over an initial period of 5-6 months. The effects are however weaker in regimes 1 and 2, although these are often precisely estimated and in policy terms they would give policymakers reasons to pursue QE policies also in moderately volatile economic environments. Finally, and consistently with the results in Section 5, the MEP leads to the strongest yield responses, with the same qualitative patterns as QE but with considerably higher estimates, across all regimes. In the case of the MEP, also IGST corporate yields are affected although the effect tends to disappear in 2-3 months after a shock. However, all these remarks closely mimic those reported in Section 5.

We have repeat the GMM estimation and the ensuing IRF analysis when a second common shock is admitted that represents the lagged effect of the ADS index. Apart from minor details, the empirical definition of the regimes for identification purposes and the variances of structural residuals retrieved in this case are essentially identical to those presented in Tables 3 and 4 (panel A). An Appendix reports detailed estimation results for the case of both contemporaneous and lagged common shocks and shows that results are quite homogeneous in two cases apart for the fact that, not surprisingly, when lagged common shocks are taken into account, the coefficients loading the ADS index on the bond yields are reduced in magnitude and significance with respect to the specification without lagged common shocks. The estimated matrix $\mathbf{A}$ is shown in panel B of Table 4: visibly, coefficients are almost identical to those estimated in the model with no lagged common shock (panel A) and the precision of the estimates remains very high. An Appendix available upon request also computes and displays the IRFs for the three policies studied in this paper from the model with contemporaneous and lagged common shocks. The IRFs are practically unchanged vs. Figure 5 and require no additional comments.

In conclusion, we obtain evidence that the introduction of one single common shock, as per equations (7)-(8), is sufficient to ensure that the assumption of orthogonality of the structural residuals is satisfied. Nevertheless, the matrices $\mathbf{A}$ and $\mathbf{B}_0$ obtained under this specification are similar to those retrieved from the baseline model in Section 5, so that the responses estimated by the IRFs are analogous. However, this alternative specification allow us to isolate in a more clear way the embedded inflationary expectations effects of QE: this is emphasized by the IRFs that now describe declining responses—this is especially clear for IGST yields—to shocks, in contrast to MEP, that instead fails to trigger strong inflationary expectations reactions and hence may turn out to be more effective over medium-long term horizons.

5.2 Spread analysis

To gain additional insights on how different types of monetary policies may affect corporate bond yields and hence affect real investment decisions, we have also analysed the response of bond yields: policy measures may affect rates in two ways, either by changing the risk premia required to buy bonds or by altering the value of time, i.e., the riskless interest rate. However, it is possible that a policy may be effective on one side of the spectrum (and we know that both QE and to some extent also MEP did reduce the riskless interest rates at the long-end of the maturity spectrum, while conventional policies do that by construction) but cause perverse effects on the other side. However, QE and MEP could have been successful in stimulating the economy by lowering the general level of interest rates, as the economic recovery gains traction, most standard asset pricing models imply an associated reduction not only in the compensation demanded by investors for expected default risk, but also in the average price of bearing exposure to corporate credit risk, above and beyond the compensation for expected defaults—that is, a reduction in the default risk premium. This increase in investor risk appetite—by lowering the price of default risk—should put additional downward pressure on corporate borrowing rates and thereby further stimulate business fixed investment.

A corporate bond spread is the difference between the bond yield and a maturity-matched risk-free rate. Although defining what a riskless asset may actually be remains problematic to some extent, for the purpose of our analysis, we shall consider U.S. Treasury yields as risk-free and therefore we will compute corporate bond spreads as the difference between corporate yields and Treasury yields of similar maturity. Hence, for each recorded corporate bond trade as recorded in TRACE, the credit spread is calculated as the difference between the yield of the corporate bond and the yield of a Treasury bill or note with a maturity which approximately matches the remaining life of the bond.[24] Next, we average the spreads of all the bonds traded in each week for each of the four portfolios defined (as in the analysis with yields, see Section 3). We note that this methodology based on the trade-by-trade calculation of spreads is more accurate than simply taking the difference between corporate yield averages and Treasury rates (see Lin and Curtillet, 2007, for a discussion of this aspect).

An Appendix available upon request shows the VAR(1) parameters in a (covariance stationary, as shown by an analysis of the roots of the characteristic equations) model for corporate and Treasury spreads:[25] more than a half of the coefficients is significant. As in the

[24] We discretize the remaining time-to-maturity of each corporate bond in the following categories, by selecting the closest from the list: 1 month, 3 months, 6 months, 1 year, 2 years, 3 years, 5 years, 7 years, and 10 years. Then, we match such imputed maturity with the Treasuries of identical maturity.

[25] The model contains eight endogenous variables, i.e., the 1-month T-bill rate along with seven corporate and government bond yield spreads. Therefore 4 of the spreads concern corporate bonds and are obtained

baseline model for the bond yields, the corporate spread series display a significant forecasting power for each other, while the non-investment grade corporate yields have significant predictive power for Treasuries. The resulting regime definition appears once more to be robust to replacing the yield with the spread series: regime 1, i.e., the tranquil state, is characterized by low mean rates but intermediate average spreads; regime 2, i.e., the transient state, is characterized by high mean rates and low mean spreads; regime 3, i.e., the crisis state, is associated to medium mean rates but high mean spreads, once more as typical of a crisis state. The estimated residual variance are sorted across regimes in the way already exposed in Section 5, with the variance of the residuals increasing when we move from regime 1 through 3. The matrix of residual variances of the structural innovations is shown in the Appendix 5 and it is essentially identical to Table 2, reported with reference to the baseline model case. The estimated matrix $\mathbf{A}$ is reported in Table 5: the major differences with respect to the baseline model is that the long-term Treasury spread display a positive contemporaneous association with the spread of investment grade bonds, both short- and long-term ones. This means that the entire Aa-Aaa cluster moves together in terms of differentials vs. riskless, matching bonds.

We proceed with the computation of IRFs, that are reported in Figures 6-8. In general, the results obtained for corporate credit spreads are homogeneous with those discussed in Figures 2-4. Yet, we can emphasize two isolated exceptions to this general finding. The effect of a conventional monetary expansion for the IGLT spread is larger in all the three regimes, especially in the crisis state, than the response of the IGLT spread. While the difference may be due to imprecise estimates in the two applications, in this respect monetary policy has a large impact on risk premia, which is reassuring. Second, the sign of the responses of the IGST spreads are now sensible in response to the QE program than they were in total terms, as the peak effect in absolute terms occurs at around the 15th week (a decrease of 8 bps) and then the IRF increases and stops being precisely estimated. In summary, the effects on the spreads are overall similar to those on yields in our baseline model. Results are clearer in terms of the rationality of the direction of the responses for IGST and, in general, of a larger magnitude. As in the baseline case, a conventional, expansionary monetary policy triggers an *increase* in corporate spreads, which is consistent with policy rates reacting to adverse news to economic fundamentals which signal a deterioration in the outlook for credit quality, reflecting a downward revision to future growth prospects. As a result, the credit spread may increase while longer-term risk-free rates decline.[26]

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in the way described in the main text and the remaining three are term spread inferred from the term structure of riskless interest rates, computed as a difference between long-term and 1-month yields.

[26] This is consistent with the result that in Figure 6 the negative relationship between changes in short rates and spreads is most pronounced for lower-rated corporate credits, a segment of the market that was especially vulnerable to adverse macroeconomic shocks during the early stages of the GFC.

In any event, there is no doubt that unconventional monetary policy in the U.S. could be expected to affect corporate bond risk premia in desirable directions. If any, there is evidence that such effects are generally and persistently sensible as they go in the appropriate directions, occasionally even more than it is the case for the overall level of yields, probably reflecting more complex effects on other, relevant risk premia that however our data do not account for.[27]

6 Conclusions

We have tested the effects of conventional monetary policy, quantitative easing, and of maturity management policies on the yields of U.S. corporate bonds at different tenors and two key rating classes. We do so by exploiting a heteroskedasticity-based identification methodology proposed by Rigobon (2003), and using the method of moments to estimate the parameters of a regime-switching structural VAR. The dynamic responses of private debt to the simulated policies are in general statistically significant in all regimes, although they are always stronger in what we have labelled as the crisis state, i.e., the regime in which the (residual) volatilities are the largest. As shown by Gourio (2013), the pricing of a corporate bond reflects not only the risk linked to the credit-worthiness of the issuer, but also a risk connected to a disaster probability. Because during a crisis this component may increase, in contrast with the stated objectives of policymakers, an expansionary monetary policy may lead to a generalized increase, rather than a decrease, of corporate yields. This can also be a consequence of the inflationary expectations that this policy may trigger through a classical monetarist channel: because conventional policies affect (increase) the monetary base, these are expected to be transmitted over time to prices and hence to cause an increase in nominal interest rates; the expectation of a monetary tightening creates business cycle risks that explain the increase in corporate rates.

The responses to QE are instead strongly persistent and go in a desirable directions. The effect on investment grade long-term yield is a significant decrease of 14 bps in the crisis state. The same holds for non-investment grade yields of the same maturity, for which the peak decline is of 45 bps. Effects are however weaker for both non- and investment grade short-term yields. Excluding the case of short-term private debt, the effects of QE are consistent with the objective of reducing the borrowing costs for firms, and results echo Gilchrist et al.'s (2015). The responses generated by MEP are instead larger, generally significant and in accordance with the direction desired by the Fed, as the program triggers a reduction in yields. For IG bonds, the decrease is of about 22 bps in the crisis state. The effects of the MEP on NIG yields are larger than QE's: short-

[27] During a crisis, IGST bonds may become illiquid and this may increase their yields above the level justified by a decline of the riskless rate as well as of the risk premia induced by QE. Hence the IRF may be less negative than the sum of the direct effects on the riskless rate and on the credit risk premium.

term yields decrease up to 70 bps and long-term yields up to 107 bps in regime 3.

Our results are robust to the introduction of common shocks and to replacing the series of total corporate yields with credit yield spreads, which measure ex-ante risk premia. Indeed, the IRFs estimated from a model for spreads show similar results vs. those obtained from the baseline model, in contrast with the mixed findings in Guidolin et al. (2017): a relatively agnostic identification scheme based on the deep properties of financial data, i.e., time-varying variances, escape the puzzling implication that monetary policies would be weakly effective because they could lead to contradictory reactions by the risk premia priced in the U.S. corporate bond market.

However, it is the case that both QE and the MEP may also have changed investors' expectations about future federal funds rates through a signalling effect. For instance, Krishnamurthy and Vissing-Jorgensen (2011) estimate the signalling effect through the magnitude of shifts of forward rates and show that this accounts for a significant portion of the decrease in 10-year bond rates deriving from QE1 and QE2. In our analysis, we have not tried to disentangle the pure effects of QE and MEP that exploit the segmented nature of the US bond market from the signalling effect and this remains an interesting avenue of research. Finally, our approach to time variation in a VAR has been based on a simple rolling-window scheme that has been mostly directed to achieve identification. However, more structural approaches remain appealing. For instance, Cuaresma, Doppelhofer, Feldkircher, and Huber (2019) and Eickmeier, Lemke, and Marcellino (2015) have developed a global (factor) VAR model with time varying parameters and stochastic volatility to analyse whether the transmission mechanism and international spillovers of US monetary policy have changed over time and test whether coefficients have evolved gradually over time or are better characterized by infrequent, but large, breaks. Similarly to our findings, they report pronounced changes in the transmission mechanism of US monetary policy, with the the strength of spillovers that has weakened in the aftermath of the global financial crisis. Their rich modelling approach could be applied to study our research question and the structure imposed provide the necessary causal identification for (nonlinear) impulse response functions to be estimated.

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Table 1

Estimated matrices $\boldsymbol{\Sigma}_\varepsilon^s$ (s = 1, 2, 3) for residuals in the VAR(1) baseline model

Assuming that the structural parameters are stable across the regimes, the table reports ML estimates of $\boldsymbol{\Sigma}_\varepsilon^1, \boldsymbol{\Sigma}_\varepsilon^2$, and $\boldsymbol{\Sigma}_\varepsilon^3$ from

$$\boldsymbol{y}_t^s = \boldsymbol{c}_1 + \boldsymbol{B}_1 \boldsymbol{y}_{t-1}^s + \boldsymbol{\varepsilon}_t^s \qquad s = 1, 2, 3$$

where $Var[\boldsymbol{\varepsilon}_t^s] = \boldsymbol{\Sigma}_\varepsilon^s$. The regimes are identified using a recursive algorithm based on the residuals of an estimated reduced-form VAR model and computing time-varying, rolling-window variances over 12-week samples for each variable: we identify a shift in regime every time the relative variances of one or several endogenous variables exceed their average value plus one standard deviation by at least a third of their standard deviation for a minimum of 24 weekly observations. We can identify 21 regimes in total, but restrict the analysis to the three "synchronized" regimes, i.e., those where at least one of the eight yield series exhibits an elevated conditional volatility, whereas all others do not show a conditional standard deviation that is abnormally low, plus a regime where all the interest rates series are in their "tranquil" zone.

	1 m T	1 y T	5 y T	10 y T	IGST	IGLT	NGST	NGLT
REGIME 1								
1 m T	0.003							
1 y T		0.001						
5 y T			0.006					
10 y T				0.007				
IGST					0.085			
IGLT						0.076		
NGST							0.703	
NGLT								1.321
REGIME 2								
1 m T	0.008							
1 y T		0.002						
5 y T			0.006					
10 y T				0.006				
IGST					0.135			
IGLT						0.586		
NGST							1.157	
NGLT								0.691
REGIME 3								
1 m T	0.041							
1 y T		0.012						
5 y T			0.018					
10 y T				0.015				
IGST					0.666			
IGLT						0.294		
NGST							18.538	
NGLT								15.027

Table 2

Estimated A matrix in the baseline model

The table reports the GMM estimates of the matrix of the contemporaneous effects **A** from the structural VAR(1) model:

$$\boldsymbol{A}\boldsymbol{y}_t = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{y}_t$ is the 8x1 vector collecting the 1-month Treasury (1mT_t), the 1-year (1yT_t), the 5-year (5yT_t), the 10-year (10yT_t), the investment grade corporate bond short-term ($IGST_t$), the investment grade corporate bond long-term ($IGLT_t$), the non-investment grade corporate bond short-term ($NGST_t$), and the and non-investment grade corporate bond long-term yields ($NGLT_t$). The 8x8 matrix **A** has diagonal elements equal to ones, while its off-diagonal elements capture the contemporaneous interactions. The vector $\boldsymbol{\varepsilon}_t$ contains the structural form shocks, assumed to have zero mean and variance $\sigma^2_{\varepsilon,i}$ i = {1, ..., 8} and to be orthogonal, contemporaneously and across time.

	1 m T	1 y T	5 y T	10 y T	IGST	IGLT	NGST	NGLT
1 m T	1.000	**0.004** ***	**0.005** ***	**0.005** ***	**0.039** ***	**0.015** ***	**0.000** ***	**−0.001** ***
		(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
1 y T	**−0.011** ***	1.000	**0.003** ***	**0.003** ***	**0.007** ***	**0.000** ***	**0.002** ***	**−0.001** ***
	(0.000)		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
5 y T	**−0.010** ***	**−0.012** ***	1.000	**0.002** ***	**0.002** ***	**−0.001** ***	**0.003** ***	**0.000** ***
	(0.000)	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
10 y T	**−0.010** ***	**−0.011** ***	**−0.013** ***	1.000	**−0.005** ***	**−0.005** ***	**0.001** ***	**0.001** ***
	(0.000)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
IGST	**0.011** ***	**0.006** ***	**0.006** ***	**0.004** ***	1.000	**−0.097** ***	**−0.022** ***	**0.016** ***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
IGLT	**0.014** ***	**0.008** ***	**0.008** ***	**0.006** ***	**−0.200** ***	1.000	**−0.020** ***	**0.008** ***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**
NGST	**0.004** ***	**0.000** ***	**−0.002** ***	**−0.001** ***	**0.016** ***	**−0.005** ***	1.000	**0.222** ***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**
NGLT	**0.002** ***	**0.008** ***	**0.014** ***	**0.012** ***	**−0.009** ***	**−0.017** ***	**−0.407** ***	1.000
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	

*, **, and *** indicate respectively the significance at 10%, 5%, and 1% level.

Table 3

Estimated matrices $\mathbf{\Sigma}_{\varepsilon}^{s}$ (s = 1, 2, 3) for residuals in the VAR(1) model with one common shock

Assuming that the structural parameters are stable across the regimes, the table reports ML estimates of $\mathbf{\Sigma}_{\varepsilon}^{1}, \mathbf{\Sigma}_{\varepsilon}^{2}$, and $\mathbf{\Sigma}_{\varepsilon}^{3}$ from

$$\boldsymbol{y}_t = \boldsymbol{c}_1 + \boldsymbol{B}_1 \boldsymbol{y}_{t-1}^{s} + \boldsymbol{D}_1 \boldsymbol{z}_t + \boldsymbol{\varepsilon}_t^{s} \qquad s = 1, 2, 3$$

where $Var[\boldsymbol{\varepsilon}_t^{s}] = \mathbf{\Sigma}_{\varepsilon}^{s}$. The regimes are identified using a recursive algorithm based on the residuals of an estimated reduced-form VAR model and computing time-varying, rolling-window variances over 12-week samples for each variable: we identify a shift in regime every time the relative variances of one or several endogenous variables exceed their average value plus one standard deviation by at least a third of their standard deviation for a minimum of 24 weekly observations.

	1 m T	1 y T	5 y T	10 y T	IGST	IGLT	NGST	NGLT
REGIME 1								
1 m T	0.003							
1 y T		0.001						
5 y T			0.006					
10 y T				0.007				
IGST					0.091			
IGLT						0.078		
NGST							0.615	
NGLT								1.336
REGIME 2								
1 m T	0.008							
1 y T		0.002						
5 y T			0.006					
10 y T				0.006				
IGST					0.135			
IGLT						0.560		
NGST							1.055	
NGLT								0.659
REGIME 3								
1 m T	0.041							
1 y T		0.012						
5 y T			0.018					
10 y T				0.015				
IGST					0.614			
IGLT						0.274		
NGST							17.968	
NGLT								15.001

Table 4

Estimated A matrix in the VAR model with one common shock

The table reports the GMM estimates of the matrix of the contemporaneous effects **A** from the structural VAR(1) model:

$$\boldsymbol{A}\boldsymbol{y}_t = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{y}_{t-1} + \boldsymbol{D}_0\boldsymbol{z}_t + \boldsymbol{F}_0\boldsymbol{z}_{t-1} + \boldsymbol{\varepsilon}_t,$$

that reflects the effect of contemporaneous ($\boldsymbol{z}_t$) and lagged ($\boldsymbol{z}_{t-1}$) common shocks, where $\boldsymbol{y}_t$ is defined as in Table 2. The common shock variable is the Aruoba-Diebold-Scotti business conditions index (ADS index) that tracks real business conditions. The vector $\boldsymbol{\varepsilon}_t$ contains the structural form shocks, assumed to have zero mean and variance $\sigma^2_{\varepsilon,i}$ i = {1, ..., 8} and to be orthogonal, contemporaneously and across time. Panel A sets $\boldsymbol{F}_0 = \boldsymbol{O}$ while panel B estimates both $\boldsymbol{D}_0$ and $\boldsymbol{F}_0$. In both panels we have boldfaced coefficients with p-value equal to or less than 0.05.

Panel A

	1 m T	1 y T	5 y T	10 y T	IGST	IGLT	NGST	NGLT
1 m T	1.000	**0.004**	**0.005**	**0.005**	**0.037**	**0.014**	**−0.001**	**−0.001**
1 y T	**−0.011**	1.000	**0.003**	**0.003**	**0.006**	**−0.001**	**0.001**	**−0.001**
5 y T	**−0.010**	**−0.012**	1.000	**0.002**	**0.002**	**−0.001**	**0.003**	**0.000**
10 y T	**−0.010**	**−0.012**	**−0.013**	1.000	**−0.005**	**−0.005**	**0.001**	**0.001**
IGST	**0.011**	**0.007**	**0.006**	**0.004**	1.000	**−0.102**	**−0.012**	**0.016**
IGLT	**0.013**	**0.008**	**0.008**	**0.006**	**−0.189**	1.000	**−0.017**	**0.008**
NGST	**0.004**	**0.001**	**0.000**	**0.001**	**0.004**	**−0.009**	1.000	**0.142**
NGLT	**0.002**	**0.007**	**0.011**	**0.009**	**−0.013**	**−0.022**	**−0.356**	1.000

Panel B

	1 m T	1 y T	5 y T	10 y T	IGST	IGLT	NGST	NGLT
1 m T	1.000	**0.004**	**0.004**	**0.005**	**0.037**	**0.014**	**−0.001**	**−0.001**
1 y T	**−0.011**	1.000	**0.003**	**0.003**	**0.006**	**−0.001**	**0.001**	**−0.001**
5 y T	**−0.010**	**−0.012**	1.000	**0.003**	**0.003**	**0.000**	**0.003**	**0.000**
10 y T	**−0.010**	**−0.011**	**−0.012**	1.000	**−0.004**	**−0.004**	**0.001**	**0.001**
IGST	**0.012**	**0.008**	**0.007**	**0.004**	1.000	**−0.103**	**−0.013**	**0.016**
IGLT	**0.013**	**0.009**	**0.009**	**0.006**	**−0.189**	1.000	**−0.018**	**0.009**
NGST	**0.003**	**0.001**	**0.000**	**0.001**	**0.010**	**−0.004**	1.000	**0.145**
NGLT	**0.002**	**0.007**	**0.010**	**0.008**	**−0.017**	**−0.027**	**−0.362**	1.000

Table 5

Estimated A matrix in a VAR(1)structural model for corporate yield spreads

The table reports the GMM estimates of the matrix of the contemporaneous effects **A** from the structural VAR(1) model:

$$\boldsymbol{A}\boldsymbol{s}_t = \boldsymbol{c}_0 + \boldsymbol{B}_0\boldsymbol{s}_{t-1} + \boldsymbol{\varepsilon}_t,$$

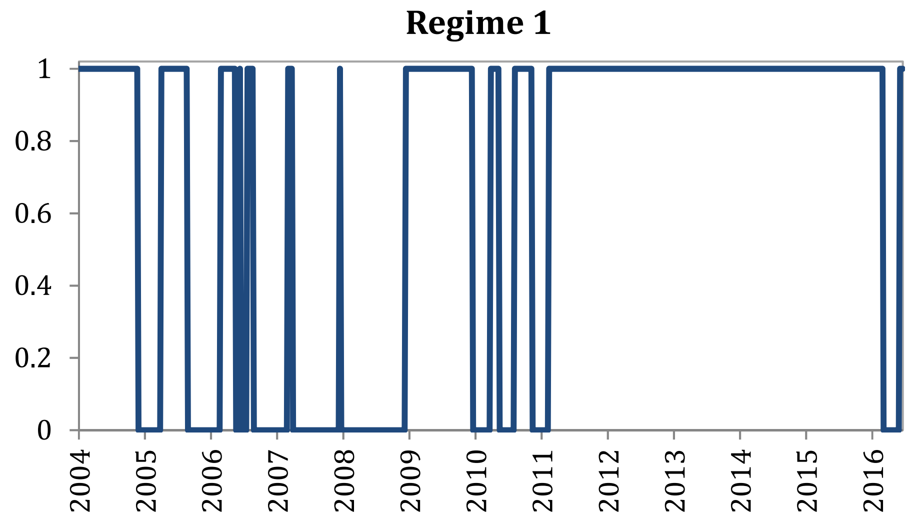
where $\boldsymbol{y}_t$ is the 8x1 vector collecting the 1-month Treasury (1mT_t), the 1-year (1yT_t), the 5-year (5yT_t), the 10-year (10yT_t), the investment grade corporate bond short-term ($IGST_t$), the investment grade corporate bond long-term ($IGLT_t$), the non-investment grade corporate bond short-term ($NGST_t$), and the and non-investment grade corporate bond long-term yield *spreads* ($NGLT_t$) defined by averaging over portfolios of credit spreads computed on a transaction-by-transaction basis, on a grid of approximate time-to-maturity points. . The 8x8 matrix **A** has diagonal elements equal to ones, while its off-diagonal elements capture the contemporaneous interactions.

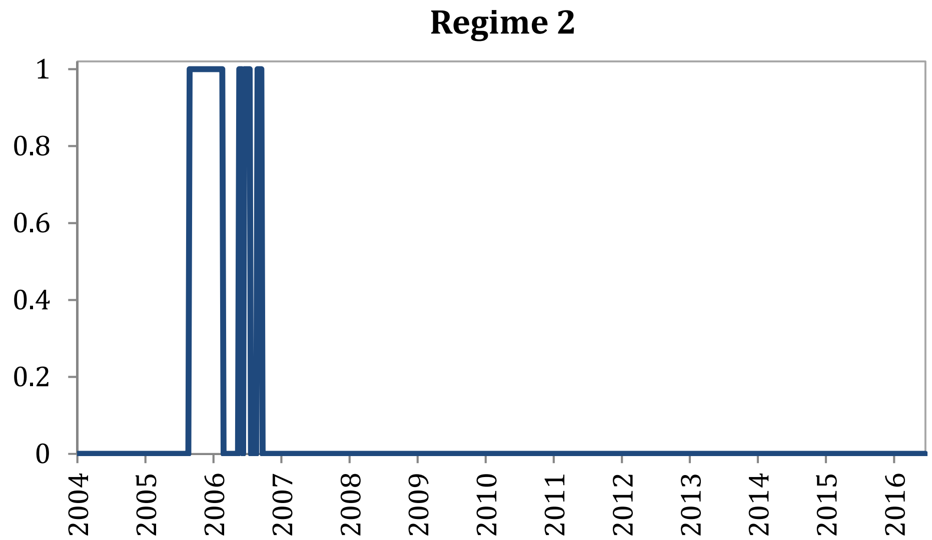
	1 m T	1 y T	5 y T	10 y T	IGST	IGLT	NGST	NGLT
1 m T	1.000	**0.004** ***	**0.005** ***	**0.005** ***	**0.038** ***	**0.014** ***	**−0.001** ***	**0.000** ***
		(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
1 y T	**−0.011** ***	1.000	**0.003** ***	**0.003** ***	**0.013** ***	**0.002** ***	**0.001** ***	**−0.001** ***
	(0.000)		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
5 y T	**−0.010** ***	**−0.012** ***	1.000	**0.002** ***	**0.010** ***	**0.006** ***	**0.002** ***	**0.000** ***
	(0.000)	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
10 y T	**−0.010** ***	**−0.011** ***	**−0.013** ***	1.000	**0.001** ***	**0.002** ***	**0.000** ***	**0.001** ***
Treasury	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
IGST	**0.010** ***	**0.008** ***	**0.010** ***	**0.008** ***	1.000	**−0.100** ***	**−0.029** ***	**0.024** ***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
IGLT	**0.014** ***	**0.010** ***	**0.011** ***	**0.008** ***	**−0.204** ***	1.000	**−0.022** ***	**0.012** ***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**
NGST	**0.005** ***	**0.000** ***	**−0.003** ***	**−0.001** ***	**0.021** ***	**0.005** ***	1.000	**0.243** ***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**		**(0.000)**
NGLT	**0.000** ***	**0.007** ***	**0.014** ***	**0.012** ***	**−0.011** ***	**−0.027** ***	**−0.414** ***	1.000
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	

*, **, and *** indicate respectively the significance at 10%, 5%, and 1% level.

Figure 1

Regimes in the baseline model





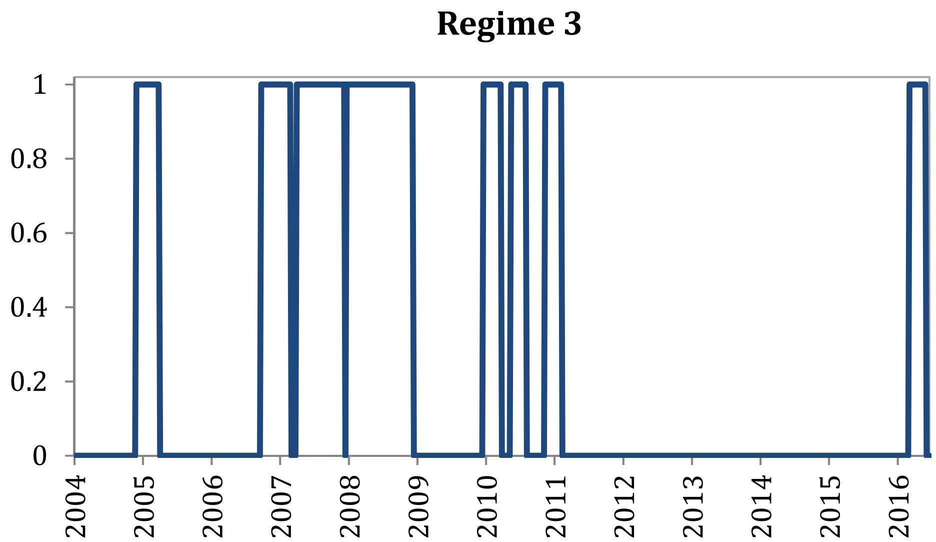


Figure 2

Effects of conventional monetary policy on corporate bond yields in the baseline model

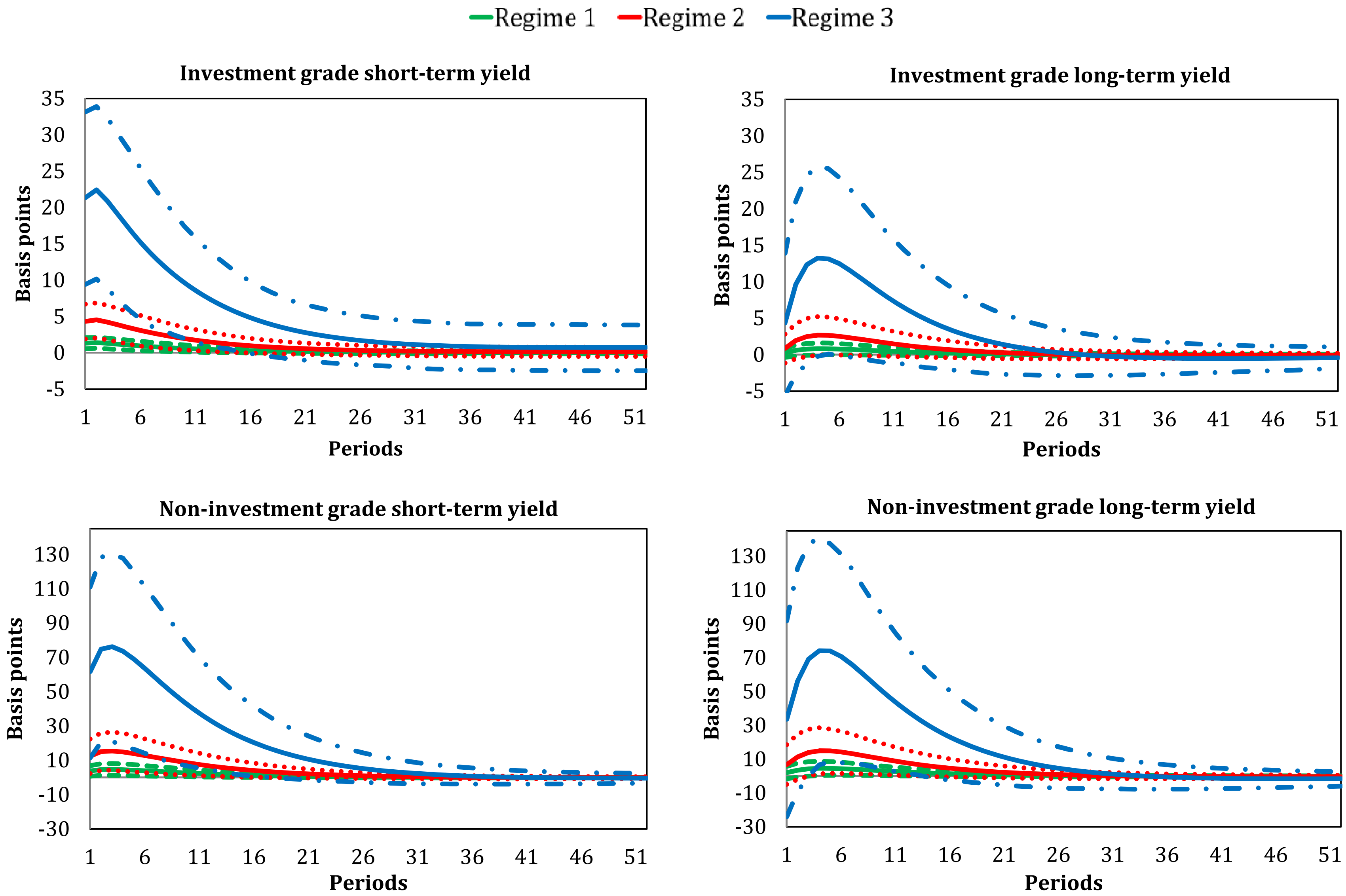


Figure 3

Effects of quantitative easing on corporate bond yields in the baseline model

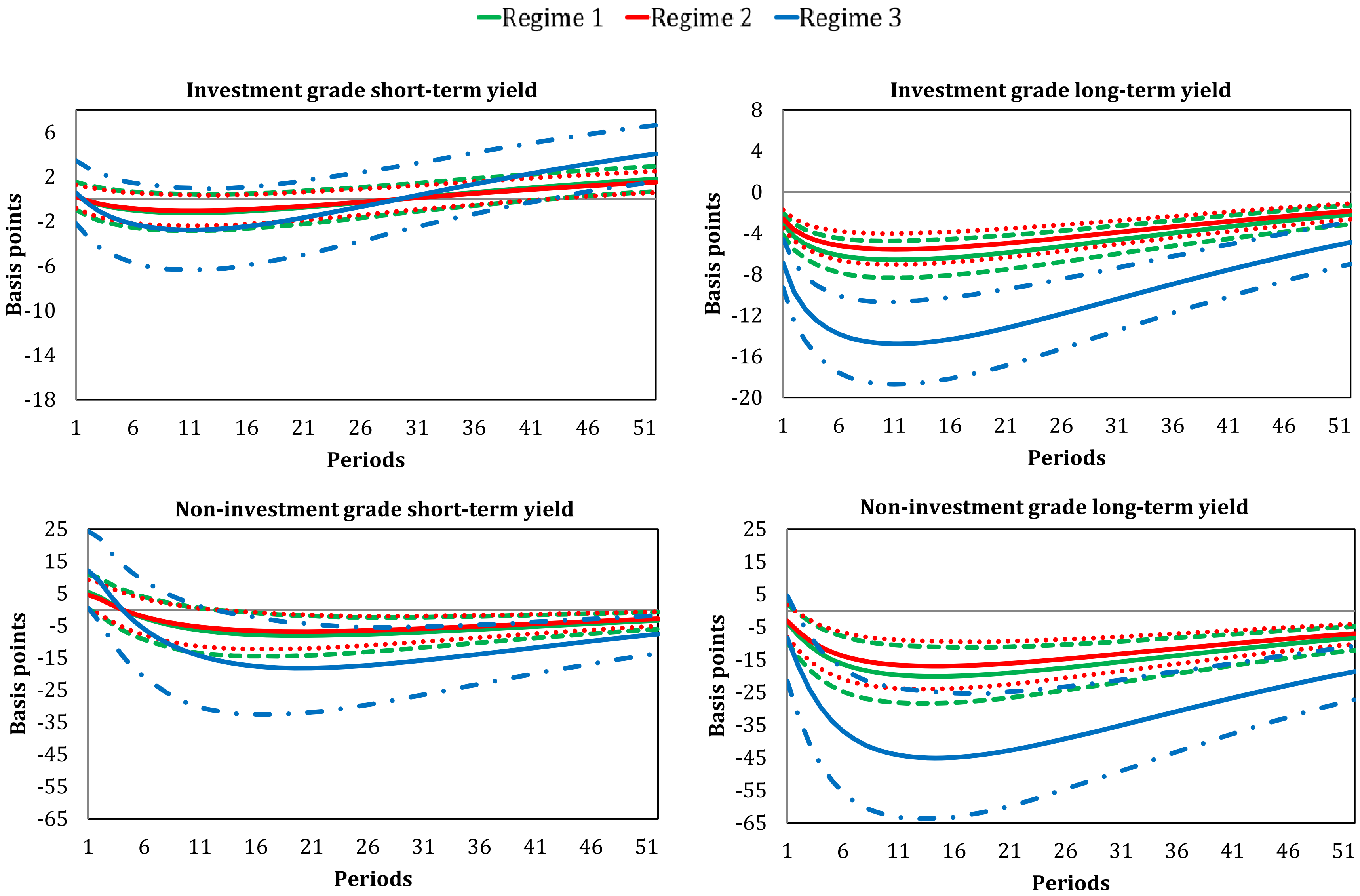


Figure 4

Operation "Twist" in the baseline model

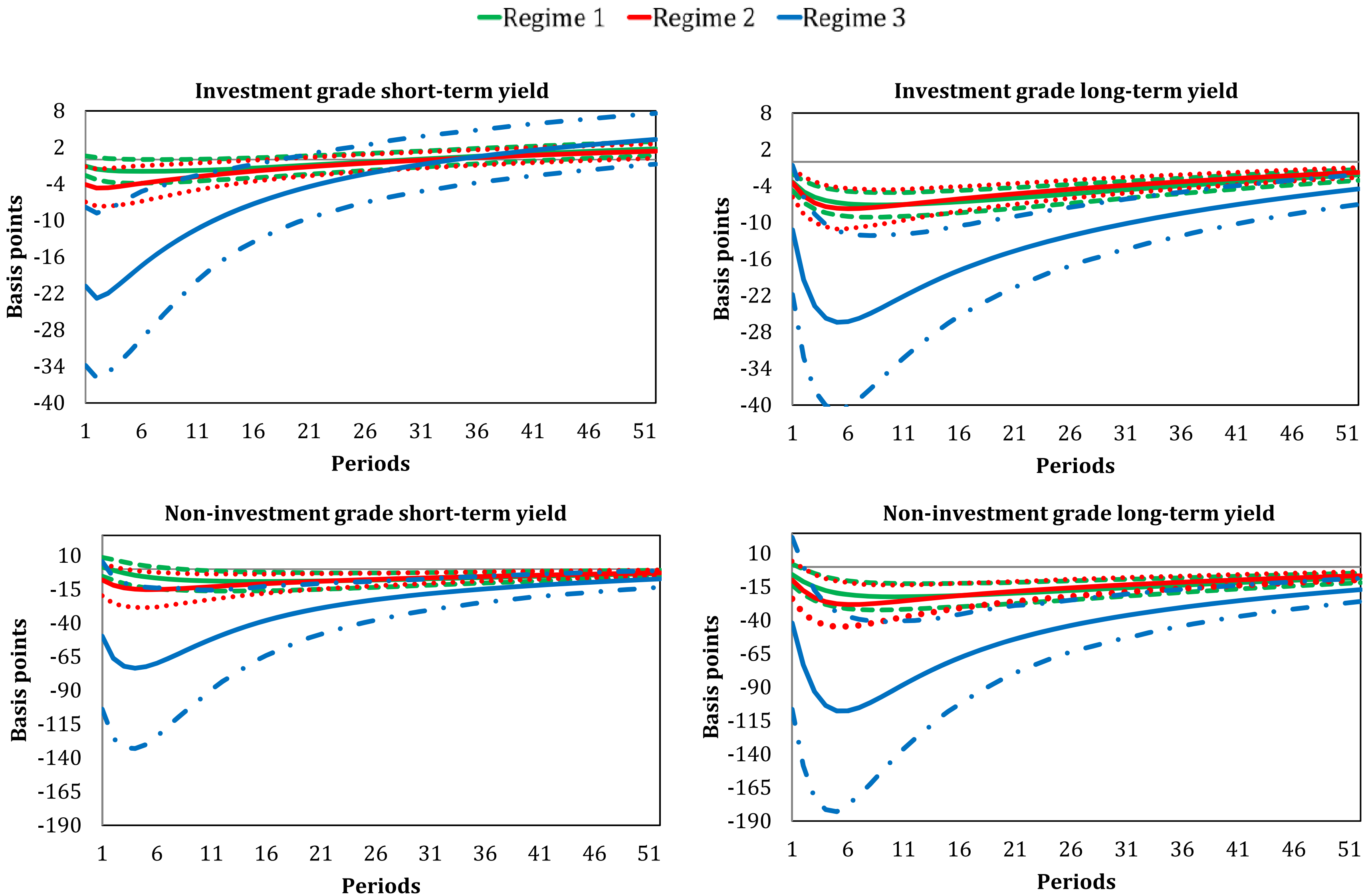


Figure 5

Impulse response functions to policy shocks in the model with one common shock

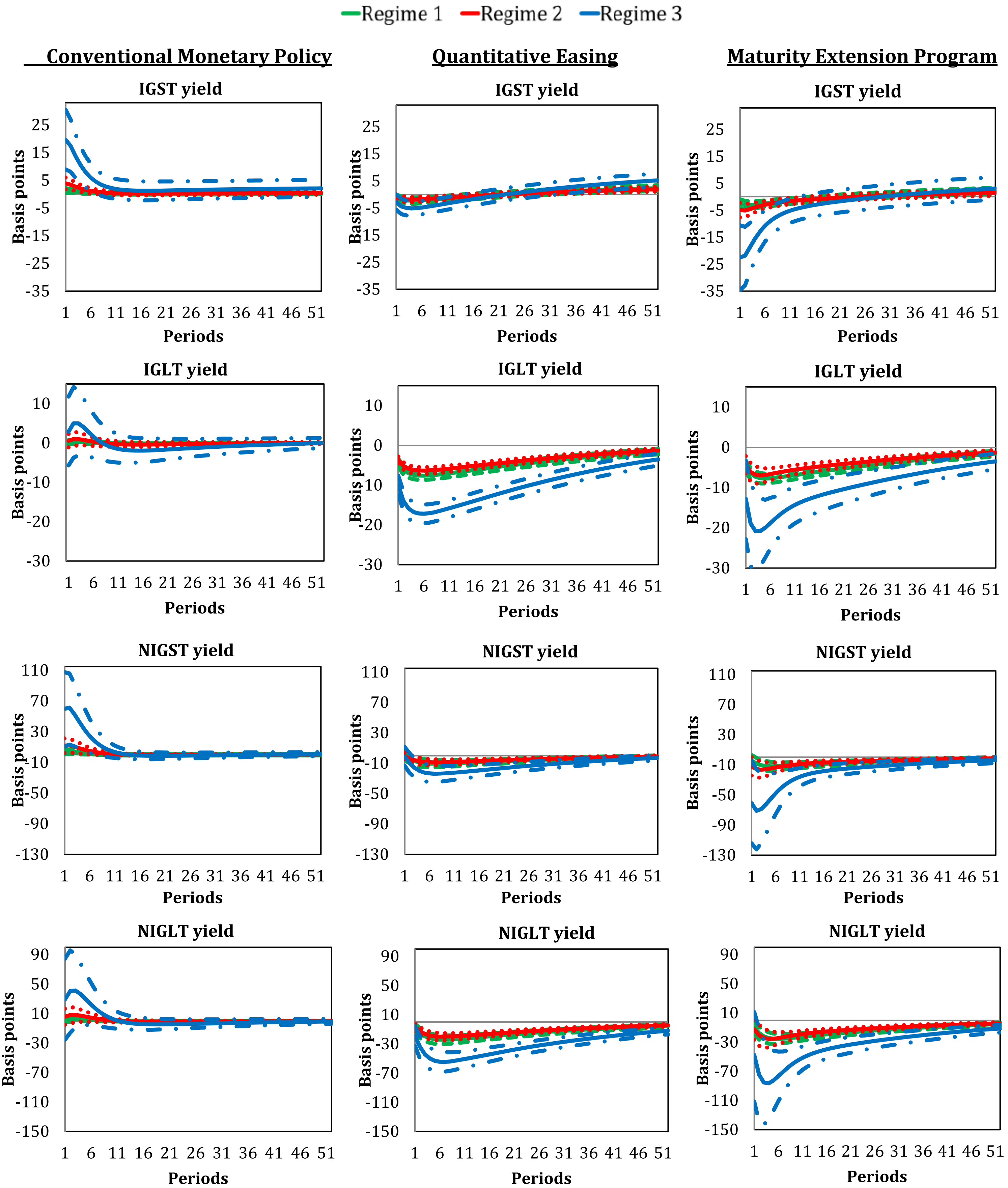


Figure 6

Effects of conventional monetary policy on corporate bond spreads in the baseline model

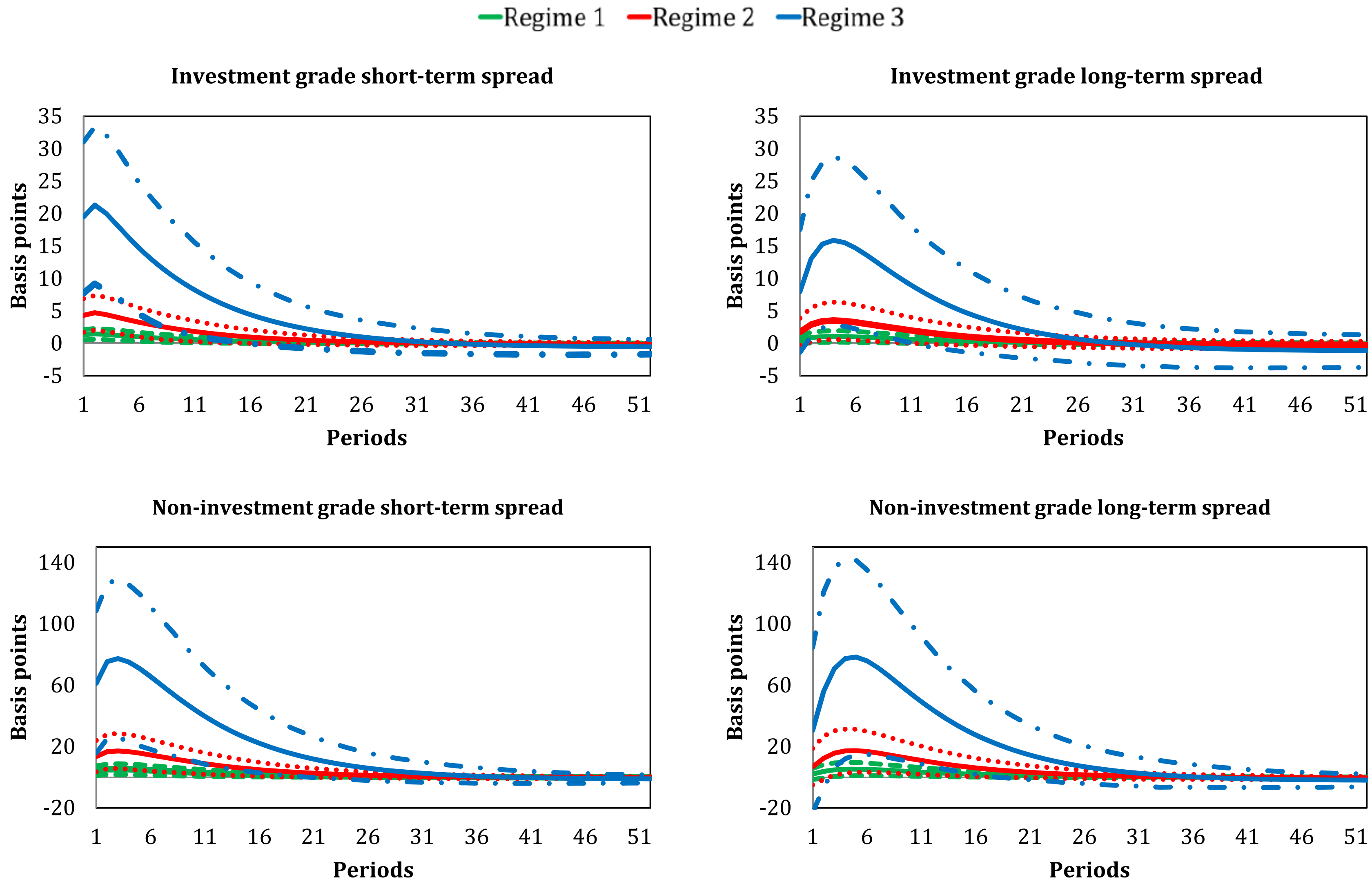


Figure 7

Effects of quantitative easing on corporate bond spreads in the baseline model

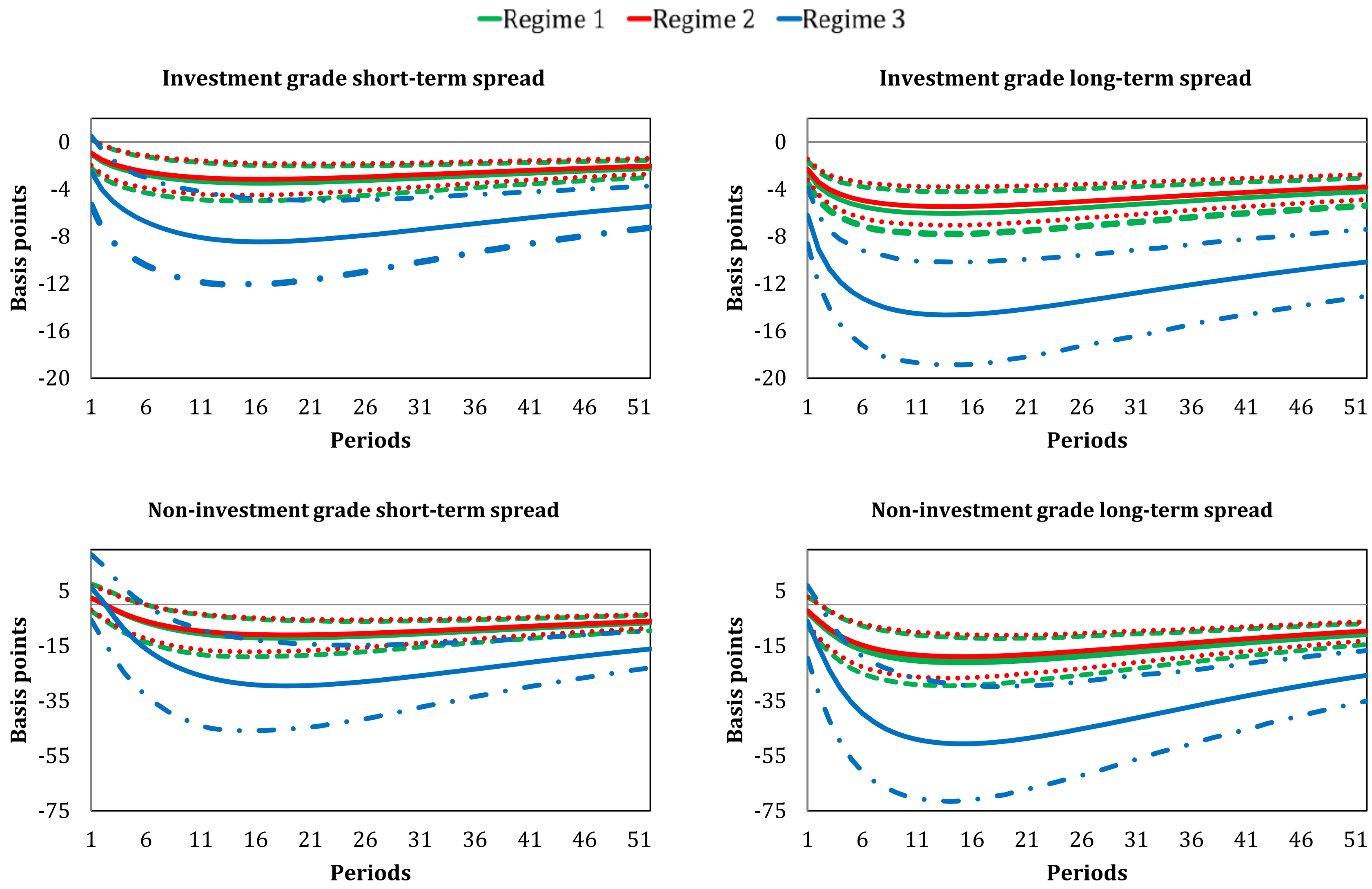


Figure 8

Effects of the maturity extension program on corporate bond spreads in the baseline model