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Do Corporate Bond Shocks Affect Commercial Bank Lending?

Mario Catalán and Alexander W. Hoffmaister

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Do Corporate Bond Shocks Affect Commercial Bank Lending?
Prepared by **Mario Catalán** and **Alexander W. Hoffmaister**

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ABSTRACT: Understanding how corporate bond market disruptions are transmitted to the rest of the financial system is essential to gauge systemic financial risk and design policy responses. In this study, we extend the vector autoregression model of Gilchrist and Zakrajšek (2012) to explicitly account for the role of commercial banks in the transmission of corporate bond credit spread shocks. We find that corporate bond market shocks can reduce commercial bank lending activity by tightening loan supply. Policies designed to contain stress in the corporate bond market can thus mitigate systemic risk by limiting contagion to the commercial banking sector.

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WORKING PAPERS

Do Corporate Bond Shocks Affect Commercial Bank Lending?

Prepared by Mario Catalán and Alexander W. Hoffmaister¹

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Introduction

How are disruptions in corporate bond markets transmitted to the rest of the financial system and real economic activity? Answering this question is crucial to gauge systemic financial risk and design policy responses to crises. The systemic importance of corporate bond markets became evident during the COVID-19 crisis, when fear of large spillovers from market strains prompted the US Federal Reserve to purchase corporate bonds for the first time in its history (Gilchrist et al., 2020; Sharpe and Zhou, 2020; O'Hara and Zhou, 2021; Falato et al., 2021; Haddad et al., 2021).

Motivated by theories that establish a link between the quality of borrowers' balance sheets and their access to external finance (Bernanke and Gertler 1989; Kiyotaki and Moore, 1997; Bernanke et al., 1999), a large empirical literature uncovers a significant relationship between credit spreads and economic activity. Gilchrist and Zakrajšek (2012, henceforth GZ) decompose corporate bond credit spreads into default risk and excess bond premium components and find the latter to be a particularly powerful predictor of economic activity. Using a vector autoregression (VAR) model, they show that an increase in the excess bond premium leads to significant declines in output and equity valuations despite reductions in policy and treasury interest rates.

We extend GZ's empirical VAR framework to explicitly account for the role of commercial banks in the transmission of corporate bond credit spread shocks and address the following questions: How do excess bond premium shocks affect commercial bank lending? Do commercial banks act as conduits for the transmission of these shocks? Does the inclusion of commercial banking variables in the VAR model affect the estimated responses of output, consumption, and investment to excess bond premium shocks?

Combining insights from the literature on the intertwined activities of banks and markets, in this paper we conjecture that explicitly accounting for commercial banking activity could potentially affect the identification of corporate bond credit spread shocks in a GZ-type VAR framework and provide additional insights into their transmission mechanism.¹

In particular, a corporate bond credit spread shock could affect commercial banks through multiple channels. Non-financial firms could seek to substitute bond issuance for bank debt, thus boosting the demand for commercial bank loans. However, since commercial banks also issue debt securities, the shock could increase banks' funding costs and prompt a tightening of loan supply. In addition, the contractionary effect that a credit spread shock exerts on economic activity could exacerbate commercial banks' credit losses and dampen loan demand. As commercial banking activity relies to some extent on a well-functioning corporate bond market and can influence real economic activity, quantifying the impact of corporate bond shocks on output requires accounting explicitly for the commercial banking sector.

¹ One strand of this literature considers the substitutability between bond and bank debt financing for non-financial firms (Becker and Ivashina, 2014, and references therein). Another strand focuses on the extent to which banks finance themselves with non-deposit debt (Huang and Ratnovsky, 2011, and references therein).

Our main contributions are as follows. First, we provide empirical evidence that corporate bond market shocks can generate significant contagion to the commercial banking sector. We find that an excess bond premium shock triggers a reduction in real bank lending (quantity) and an increase in the real bank lending rate (price). This implies that the effect of the corporate bond shock on commercial banks' loan supply must more than offset its effect on loan demand. We thus conclude that commercial banks act as conduits for the transmission of corporate bond credit spread shocks, and these shocks predominantly affect the supply of bank loans. We further substantiate this conclusion by using Call Report micro data to examine whether banks' responses depend on their exposure to the corporate bond market (as proxied by their reliance on non-deposit funding). We find that banks with high exposure to the corporate bond market reduce lending more aggressively than banks with low exposure.

Our results suggest that, unchecked by policy interventions and backstops, a 20 basis point (one standard deviation) shock in the excess bond premium results in a 4 percentage point contraction in the level of real commercial bank lending and a 40 basis point increase in the real lending rate after six to eight quarters. Larger corporate bond shocks could thus pose a threat to system-wide stability. This evidence can serve to justify the imposition of macroprudential regulations on non-banks, or the deployment of liquidity backstops such as those established by central banks during the "dash-for-cash" episode in March 2020.²

Second, we confirm the need to augment the GZ VAR model to include commercial banking variables (bank lending and lending interest rate) through a battery of tests, including Granger causality and Sims exogeneity tests for omitted variables in VARs, and tests of "fundamentalness" (Canova and Hamidi Sahneh, 2018; Forni and Gambetti, 2014). We show that adding these variables to the GZ VAR improves the forecast performance of the model substantially, reducing the root mean square errors of forecasts for consumption, investment, and output by 10-15 percent and those for other variables up to 50 percent at four to eight quarter horizons.

In principle, the omission of commercial banking variables and use of a shorter sample period (1972:Q4-2010:Q4), not fully covering the recovery phase of the bank credit cycle following the global financial crisis in the GZ study, could lead to substantial differences in the estimated impulse responses functions (IRFs). We find, nonetheless, that these modifications do not have major effects on either the identification of excess bond premium shocks or the responses of output, consumption, and investment to these shocks. That is, we verify that the key results of the GZ study are robust to the inclusion of commercial banking variables and a nine-year extension of the sample period. The modifications of the GZ model in this study, however, highlight the importance of the commercial banking sector in the transmission of corporate bond credit spread shocks.

² In March 2020, the average credit spread of corporate bonds widened more than 200 basis points in less than 10 days. The swift actions taken by the US Federal Reserve restored investors' confidence (Gilchrist et al., 2021). Our results suggest that these interventions prevented contagion to commercial banks, which could have had severe consequences for the real economy. Future policy and regulatory initiatives should focus on mitigating vulnerabilities of corporate bond dealers and investment funds that reduce their risk-bearing capacity during periods of stress. They should seek to limit the possibility that central banks need to act as market makers of last resort in support of the corporate bond market. For discussions and analytical frameworks on central bank interventions in securities markets, see Buiter and Sibert (2007), King et al. (2019), and Hauser (2021).

This paper is closely related to the influential GZ contribution, which builds on prior research documenting the importance of credit spreads for real economic activity.^{3,4} In the GZ study, the decomposition of credit spreads into excess bond premium and default risk components allows an interpretation of excess bond premium shocks as credit supply shocks that reflect reduced risk-bearing capacity of the financial sector.

Our paper is also related to recent studies which have uncovered factors that reduce the risk-bearing capacity of corporate bond dealers and mutual funds. Adrian et al. (2017) show that a tightening of dealers' balance sheet constraints—including those caused by regulatory changes implemented after the global financial crisis—can impact bond market liquidity and credit spreads. In particular, they document that bonds traded by balance-sheet-constrained dealers tend to be less liquid. Friewald et al. (2012) show that liquidity explains roughly a third of the time variation in aggregate corporate bond yield spreads in normal times, and about half of the time variation during crises. In addition, the liquidity transformation of investments by mutual funds makes them vulnerable to runs triggered by coordination failures (Chen et al., 2010; Goldstein et al., 2017; Falato et al., 2021). Runs on funds, in turn, can trigger fire sales of corporate bonds and a widening of credit spreads (Jiang et al., 2022). In our extension of the GZ framework, a credit supply disruption originated in bond dealers or mutual funds manifests itself as an excess bond premium shock.

In connection to this literature, we offer two new insights: (i) commercial banks are vulnerable to contagion from shocks originated in the corporate bond market; and (ii) commercial banks play an important role as conduits in the transmission of excess bond premium shocks to real economic activity.

In addition, this paper relates to the literature which examines the interplay of corporate bond financing and bank debt financing with economic activity (Becker and Ivashina, 2014, and references therein). That literature shows that negative bank credit supply shocks can affect bond markets because (some) non-financial firms can substitute loan for bond debt financing. A well-functioning bond market can thus act as a “spare tire” for the commercial banking system, helping to attenuate the impact of a bank credit crunch on real economic activity. That literature, however, does not consider the causal links in the opposite direction: how shocks originated in the corporate bond market can affect commercial banks' lending activity.

³ Research prior to Gilchrist and Zakrajšek (2012) had documented the importance of corporate bond spreads as predictors of US economic activity (Gertler and Lown, 1999; Gilchrist, Yankov, and Zakrajšek, 2009 and references therein). The spreads between long- and short-term Treasury rates (term spreads) and the commercial paper-Treasury bill spreads are also found to have predictive content for US real economic activity. Frequently cited studies on the role of term spreads include: Harvey (1988), Estrella and Hardouvelis (1991), Estrella and Mishkin (1996, 1998), Hamilton and Kim (2002), Stock and Watson (2003), Ang, Piazzesi, and Wei (2006), and Wright (2006). Common references on the predictive content of commercial paper-Treasury bill spreads include: Friedman and Kuttner (1992, 1998) and Emery (1996).

⁴ Faust, Gilchrist, Wright and Zakrajšek (2013) note that the predictive power of the commercial paper-Treasury bill spread was substantial in the 1970s and 1980s but vanished afterwards. The predictive ability of high yield (“junk”) bond credit spreads has also been uneven across time, in part because the spread indicators used in the literature aggregated information corresponding to bonds with different characteristics (duration, credit risk, etc.). “Cleaner” corporate bond credit spread measures, such as those presented in Gilchrist and Zakrajšek (2012), were needed to uncover more stable relations between corporate bond spreads and economic activity.

Greenspan (1999a, 1999b) proposed the so-called “spare tire” hypothesis after Russia’s sovereign default in 1998, when US bond markets seized up and commercial banks were able to replace the intermediation function of public capital markets. In this episode, bond issuance fell but commercial banks accelerated lending, acting as a “spare tire” for bond markets. Greenspan notes, however, that commercial banks became more risk averse but increased lending because of previously committed credit lines and monetary policy easing by the Federal Reserve, which were sufficient for commercial banks to effectively backstop bond markets.

In this paper, we present econometrics-based evidence—using data spanning over 40 years and covering a wide range of crisis episodes—that points to the opposite conclusion: commercial banks cannot be expected to serve as a “spare tire” when corporate bond markets seize up. As noted above, corporate bond credit spread shocks cause an increase in real bank lending rates that is larger than the widening of the excess bond premium, implying that non-financial firms with access to both types of financing sources would still prefer to issue bonds rather than take on additional loans. These findings are consistent with those of Adrian et al. (2013), who use a discrete choice framework and micro-level data on new loans and bonds issued by non-financial US corporations to document that an increase in the excess bond premium reduces the probability of loan issuance.

The rest of this paper is organized as follows. Section II defines the GZ and extended VAR models and discusses their empirical estimation and the identification of excess bond premium shocks. Section III performs tests to examine whether the GZ VAR model should be extended to include banking sector variables; it also compares the forecast performance of the GZ and the extended models. Section IV presents the impulse response functions for an excess bond premium shock generated by the extended model. Section V concludes.

VAR Model

Consider an “extended” VAR model with n variables, consisting of n_b banking sector variables and the n_{GZ} variables in the GZ VAR model:

$$\mathbf{y}_t = \mathbf{A}(L) \cdot \mathbf{y}_t + \mathbf{e}_t,$$

where \mathbf{y}_t is a $n \times 1$ vector and $n = n_b + n_{GZ}$; $\mathbf{A}(L)$ is a lag polynomial of order p ,

$\mathbf{A}(L) = \mathbf{A}_1 \cdot L + \mathbf{A}_2 \cdot L^2 + \dots + \mathbf{A}_p \cdot L^p$, where the matrices \mathbf{A}_s contain the model’s coefficients for lags $s = 1, \dots, p$; and \mathbf{e}_t is a vector of reduced-form shocks with $E[\mathbf{e}_t \cdot \mathbf{e}_t'] = \mathbf{\Omega}$. Define the structural (orthogonal) shocks as $\boldsymbol{\varepsilon}_t = \boldsymbol{\Lambda}^{-1} \cdot \mathbf{e}_t$, where $\boldsymbol{\Lambda} \cdot \boldsymbol{\Lambda}' = \mathbf{\Omega}$.

We collect the banking sector variables in the vector $\mathbf{y}_t^b = [dl_t \quad i_t^L]'$, where dl denotes the change in the log of commercial banks’ lending (in real terms), and i^L is the (average) commercial banks’ nominal lending rate. The GZ VAR variables are collected in the vector

$\mathbf{y}_t^{GZ} = [dC_t \ dI_t \ dY_t \ dP_t \ ebp_t \ esr_t \ i_t^{10y} \ i_t^{FF}]'$, where (i) dC denotes log-difference of real personal consumption expenditure; (ii) dI denotes log-difference of real business fixed investment; (iii) dY denotes log-difference of real GDP; (iv) dP measures inflation as the log-difference of the GDP price deflator; (v) ebp is the quarterly average of the excess bond premium; (vi) esr is the quarterly (value-weighted) excess stock market return; (vii) i^{10y} denotes the 10-year (nominal) treasury yield; and (viii) i^{FF} is the effective (nominal) federal funds rate.

The identifying assumption implied by the recursive ordering of variables in the VAR model is that a shock to the excess bond premium (ebp) can only affect economic activity (dC, dI, dY) and inflation (dP) with a lag, while the excess stock market return (esr), the federal funds rate (i^{FF}), the 10-year treasury yield (i^{10y}), and the banking sector variables (\mathbf{y}_t^b) can react contemporaneously to such a shock.

The VAR model is estimated with two lags (as in the GZ study) using quarterly data for the period 1972:Q4 to 2019:Q4. All the data were obtained from the *FRED* database, except for the stock market return series, which comes from *Global Financial Data* and ebp that is published on the Federal Reserve's webpage. See Appendix I for further details on data sources and transformations.

Should Banking Sector Variables be Included in the GZ VAR Model?

We divide this broad question into three interrelated questions.

a) Are the GZ model's residuals correlated with banking sector variables?

To the extent that banking sector variables are relevant for the VAR analysis, they should be correlated with the reduced-form shocks of the GZ VAR model that omits them (Canova, 2009). Table 1 shows the correlation coefficients of bank lending and the lending rate with the reduced-form residuals from the GZ VAR model, along with results of Ljung and Box (1978) tests that evaluate their statistical significance.

Panel A shows that the correlations of bank lending with the reduced-form residuals of the GZ model range from +0.29 to -0.11. The corresponding Ljung-Box tests point to statistically significant correlations (at the 10 percent significance level) of bank lending with consumption, output, and the federal funds rate. Note that except for consumption, these correlations are not significant when the contemporaneous correlation is excluded. Panel B shows the correlations of the lending rate with the residuals of the GZ model equations. These range from +0.07 to -0.02 and in contrast to the case of bank lending, the Ljung-Box tests do not reject the null hypotheses of no correlation.

b) Does the inclusion of banking sector variables improve the model's forecast performance?

We compare the forecast performances of the GZ and extended models using as our metric the root mean square error (RMSE) of the out-of-sample forecasts for the last 48 quarters in the sample period.

Table 2 presents the results for the extended models that respectively include bank lending (panel A), the lending rate (panel B), and both banking variables (panel C). The table shows the percent reductions in RMSEs of forecasts generated from the extended model relative to those generated from the GZ model.

The accuracy of the forecasts for all the variables improves substantially when bank lending is added to the GZ model (panel A): it reduces the RMSEs of forecasts for consumption, investment, and output by 10-15 percent and those of other variables up to 50 percent at four to eight quarter horizons. For longer-term forecasts, the reductions in RMSEs remain large for the GDP deflator, the 10-year treasury yield, and the federal funds rate. Similar patterns and comparable improvements in forecast performance emerge when the lending rate is added to the model (panel B), and when both banking variables are added jointly (panel C).

c) Is there evidence of missing variables and/or lack of "fundamentalness" in the GZ model?

We turn to formal tests to assess the need of augmenting the GZ model by including banking variables. First, we perform standard Granger-causality and Sims (1972) exogeneity tests for omitted variables in VARs, applying them both to individual equations and the system as a whole. And second, we evaluate the "fundamentalness" of the GZ model using recently developed tests (Forni and Gambetti, 2014; Canova and Hamidi Sahneh, 2018).

The test results are presented in Table 3.⁵ Consider first the Granger-causality and Sims exogeneity tests when we only add bank lending to the GZ model (panel A). The system-wide Granger causality test rejects the null hypothesis of no causality from bank lending to the variables in the GZ model at the 5 percent level. Though less informative, tests for individual equations indicate that bank lending Granger-causes consumption and the federal funds rate. Also, the system-wide Sims exogeneity test rejects the hypothesis of unidirectional causality of all the GZ variables on bank lending—that is, the GZ variables cannot be considered "exogenous" to bank lending. The Sims exogeneity tests for individual GZ variables do not, however, reject unidirectional causality.

Consider next adding the lending rate to the GZ model (panel B). In this case, the system-wide Granger causality test also rejects the absence of causality. And individual equation tests indicate that the lending rate Granger-causes all the variables in the GZ model, except for consumption, the excess bond premium, and excess stock market return. The system-wide Sims exogeneity test, in turn, rejects exogeneity of all the GZ variables taken together to the bank lending rate. And the Sims tests based on individual GZ variables also reveal a lack of exogeneity, rejecting the hypothesis of unidirectional causality from consumption, investment, output, and the federal funds rate to the lending rate.

⁵ Appendix II describes the implementation of these tests in detail.

When we add both bank lending and the lending rate (panel C), the system-wide and equation-by-equation test results reflect a combination of the results discussed above. The banking sector variables are found to Granger-cause the variables in the GZ model and reject the exogeneity of the GZ variables vis-à-vis the banking sector variables.

In sum, the test results point to the need to include banking variables in the GZ model. Consider next the issue of whether the GZ model exhibits “fundamentalness” (Forni and Gambetti, 2014; Canova and Hamidi Sahneh, 2018). When a VAR model’s structural moving average representation is “non-fundamental,” the variables in the model do not contain enough information to recover structural shocks (that is, the “true” innovations).⁶ From a practical standpoint, however, Beaudry et al. (2019) argue that a rejection of “fundamentalness” may be explained by a “small” informational deficiency of the VAR;⁷ in this case, a sub-set of the estimated impulse responses “could” still provide useful information about the effects of structural shocks.

The implementation of the fundamentalness tests in this study differs from that in Forni and Gambetti (2014) and Canova and Hamidi Sahneh (2018). Those studies base their tests on information comprising dozens, if not hundreds, of time series—where principal components are extracted to test for fundamentalness. In contrast, our tests focus on two banking sector variables. Note, however, that a model can be found to be non-fundamental whenever the fundamentalness hypothesis is rejected, even if the test is based on a single variable.⁸

Although Canova and Hamidi Sahneh (2018) note that “fundamentalness” is a system property, Forni and Gambetti (2014) argue that even if the VAR does not contain enough information to recover all structural shocks, it could be sufficient for a single shock (or subset of shocks). In this connection, they propose a test of orthogonality of estimated structural shocks (or subsets of shocks) and external variables (or factors) that could be added to the VAR. A necessary condition for a single estimated shock to be “structural” is that it be orthogonal to the past values of variables not included in the VAR. A rejection of orthogonality would imply that the VAR model should be amended by including the variables under consideration.

The results for the Canova-Hamidi and Forni-Gambetti (orthogonality) tests are presented in Table 3. The system-wide Canova-Hamidi tests for the GZ model consistently reject the null hypothesis of fundamentalness. This is true for inclusion of bank lending, the lending rate, and

⁶ Forni and Gambetti (2014) and Giannone and Reichlin (2006) discuss the relation between fundamentalness and Granger causality. Specifically, these studies argue that a VAR model is fundamental, that is, able to recover meaningful shocks, when the variables in the model are not Granger-caused (predicted) by variables outside the model. If they are, the model should be augmented to include the relevant information. Canova and Hamidi Sahneh (2018), however, argue that Granger causality can lead to spurious results when the VAR model contains aggregate or proxy variables. In this case, a sub-component of the aggregate variable may Granger cause the aggregate variable whether the model is fundamental or not. They propose an alternative test based on a Sims exogeneity test performed on the reduced-form residuals of the VAR model, which they argue has better testing properties. The matter of whether the Canova-Hamidi test outperforms the Forni-Gambetti test is not settled (see Forni, Gambetti, and Sala, 2018).

⁷ Beaudry et al. (2019) proposes a simple diagnostic statistic to assess the quantitative implications of the missing information. Their statistic is based on the coefficient of determination (R^2) of the regression of the estimated structural shocks on the missing variables (or principal components). In a simple illustration, they report that fundamentalness can be rejected with the missing variables explaining no more than 2 percent of the variation in the structural shocks.

⁸ The reverse is not true: a non-rejection based on a limited information set is not informative about “fundamentalness.” This is because a non-rejection does not preclude a potential rejection when a broader information set is used.

both variables taken together. These test results thus provide evidence of the need to include banking sector information in the GZ model to “recover” structural innovations. In contrast, the Forni-Gambetti test results are less informative because they fail to reject the null of fundamentalness. This is because, as noted above and in footnote 8, our fundamentalness tests are based on the information contained in two banking variables, and thus, do not preclude a rejection of the null using a broader information set.

In sum, the test results presented in this section suggest that banking sector variables should be included in the VAR model and doing so leads to substantial gains in forecast performance.

Impulse Response Analysis

The IRFs to a structural *ebp* shock for our extended model (including both banking sector variables) are shown in two figures. Figure 1 shows the responses for the variables in the original GZ model, while Figure 2 shows the responses for the banking sector variables. Note that responses for variables defined as log-differences (dC , dI , dY , dP , and dl) have been accumulated and so has the response of the excess stock market return (*esr*).

In Figure 1, the IRFs are qualitatively the same as those in the GZ study.⁹ Namely, a positive shock to the excess bond premium leads to significant declines in consumption, investment, output, and equity valuations despite reductions in the policy and treasury interest rates. Moreover, we find (in unreported results) that these responses are qualitatively unchanged for the shorter sample period used in the original GZ study (1974 Q4 – 2010 Q4) that, as noted earlier, does not cover the full recovery phase of the bank credit cycle following the global financial crises.¹⁰

In Figure 2, the responses of four key variables provide insights into the transmission of an *ebp* shock to the banking sector: (real) bank lending, the nominal and real bank lending rates, and the “intermediation” spread between the nominal bank lending rate and the federal funds rate (Figure 2).¹¹

The responses of bank lending and the lending rate are large and persistent. Specifically, a 20 basis point shock leads to a 3½–4 percentage point decline in the level of bank credit after 6–8 quarters (panel a). The nominal lending rate declines by about 25 basis points (panel b) and still the “intermediation” spread widens (panel c) because the federal funds rate declines substantially more (40 basis points, Figure 1 panel g). The real lending rate increases by about 40 basis points for ten quarters (panel d) because the decline in inflation resulting from the shock more than offsets the decline in the nominal lending rate.

⁹ The 68 percent confidence intervals for the differences between the IRFs of our extended model and the GZ model consistently included zero. In this exercise, the extended model was used as the data generating process.

¹⁰ These results are available upon request.

¹¹ The IRF of the real bank lending rate is computed by deflating the IRF of the nominal lending rate with the (average) inflation rate implied by its IRF. The IRF of the “intermediation spread” is computed as the difference between the IRFs of the federal funds rate and the lending rate.

These results suggest that an *ebp* shock is partially transmitted to the real economy through a tightening of bank credit supply. This is because, for the bank lending (quantity) to decline and the real lending rate (price) to increase, the effect of the corporate bond shock on commercial banks' loan supply must more than offset its effect on loan demand.

Note that the transmission of the *ebp* shock to bank lending takes time to materialize. The responses of bank lending and the lending rate increase over time, peaking after 8-10 quarters. Transmission lags likely reflect the maturity transformation that takes place in the commercial banking system—which implies a gradual re-setting of lending rates given the staggered maturity structure of bank loans, and short-term funding costs that are impacted by the shock more rapidly.

Moreover, the variance decompositions provide evidence on the importance of *ebp* shocks for the macroeconomy and the banking sector (Figure 3). The results confirm Gilchrist and Zakrajšek's (2012) general result that these shocks account for significant portions of the variation in other variables. In addition, we find that *ebp* shocks explain a substantial share of the variation in commercial bank lending (16 percent) and the lending rate (14 percent).

In sum, the results discussed in this section suggest that the bank credit channel is an important mechanism through which *ebp* shocks are transmitted to the real economy.

Further discussion: does heterogeneity in bank exposure to the corporate bond market matter?

To gain further insight into whether commercial banks transmit *ebp* shocks through a loan supply channel, we examine whether the responses of banks vary according to their relative exposure to the corporate bond market. In principle, if an *ebp* shock is transmitted through a bank loan supply channel, banks that are more highly and directly exposed to the shock on the funding side should reduce lending more aggressively than banks that are less exposed. It is possible that less exposed banks increase their lending in response to the shock, as the effect of higher loan demand from non-financial firms seeking to substitute bank loans for bond financing more than offsets the adverse effect of increased funding costs.

To explore this matter, we proceed as follows. We use Call Report micro data to compute the non-deposit debt-to-total debt ratio for individual banks. Using this ratio as a proxy for their relative exposure to the corporate bond market, we define three groups of banks. Banks with “low” exposures are ranked below the 25th percentile of the cross-bank distribution of non-deposit debt funding shares. Banks with “high” exposure are ranked above the 75th percentile of the distribution. And banks with “medium” exposure are ranked between the 25th and 75th percentiles. For each group, and for all the banks combined, we compute the series of bank lending and lending rate.¹² See Appendix I for further details on data sources and definitions. Ideally, we would like to explore bank heterogeneity using the augmented GZ model discussed above, replacing the aggregate banking sector variables with those corresponding to each bank group. Call Report data, however, are only available starting in 2002:Q1 and the so-called “curse of dimensionality” precludes us from following this approach.

¹² At the beginning of each period, banks operating in the system are ranked according to their shares of non-deposit debt in total debt funding, and assigned to one of the three groups (“high”, “medium”, and “low” exposure). To obtain bank lending for each group, loan amounts are aggregated across all the banks in the group. Lending rates for each group are calculated as weighted averages of the lending rates of the banks in the group—where the weights are the loan shares of individual banks relative to aggregate (groupwide) lending.

Instead, we use the (small) near-VAR methodology proposed by Basu et al. (2006) to assess the heterogeneity of bank responses following an exogenous (structural) *ebp* shock (Figure 4).¹³ We find that, although the confidence bands are wider because of the shorter sample period, the responses of bank lending and real lending rate for all banks (row 1) exhibit the same basic pattern shown in Figure 2: bank lending declines and the real lending rate increases over time in response to the shock. Further, the responses for bank groups suggest that while real lending rates increase for all groups over time, only banks with “high” exposure to the corporate bond market reduce bank lending in response to the shock (rows 2 to 4).

Nonetheless, these results should be taken with caution. The near-VAR model has a limited dynamic structure: macroeconomic factors that are likely to play an integral role in the transmission of an *ebp* shock are missing from the characterization of the dynamic responses. As noted above, this is done out of necessity, as the available data are not long enough to estimate augmented GZ models. In sum, Figure 4 provides some suggestive evidence that the aggregate decline in bank lending caused by an *ebp* shock is driven by the loan supply response of banks with high exposure to the corporate bond market.

Conclusion

We extend the empirical framework of Gilchrist and Zakrajšek (2012) to account for the role of commercial banks in the transmission of corporate bond credit spread shocks. Our analysis, based on a longer sample period that includes the full recovery phase of the bank credit cycle following the global financial crisis, allows us to empirically tease out the role of commercial banks as conduits of corporate bond credit spread shocks. We showed that excess bond premium shocks in the corporate bond market can trigger a reduction in commercial bank lending activity consistent with a tightening of loan supply. By showing evidence of contagion from the corporate bond market to commercial banks, this study sheds light on how systemic risk can propagate within the financial sector, from non-banks to commercial banks. It also suggests that the importance and value of crisis containment policies such as those deployed in the March 2020 “dash-for-cash” episode are high.

¹³ A three equation near-VAR model is estimated for each bank group. The first equation regresses the (exogenous) *ebp* shock on a constant. The other two equations regress the real bank lending growth and nominal lending rate on their own lags, the lags of the other banking variable, and the *ebp* shock. The sample consists of quarterly data for the period 2002:Q1-2019:Q4. SUR techniques are used to estimate the near-VAR following Basu et al. (2006).

Table 1. Correlation of Banking Sector Variables with Residuals of the GZ Model

| Banking variable | Reduced-form residuals in the GZ model equation for: | | | | | | | | |
|---|--|---------------------------------|--------|--------|--------|--------|-----------|----------|--|
| | dC | dI | dY | dP | ebp | esr | i^{10y} | i^{FF} | |
| A. Bank lending growth (dl) | | <i>Correlation coefficients</i> | | | | | | | |
| lag 0 | 0.165 | 0.007 | 0.160 | -0.085 | 0.080 | -0.057 | 0.099 | 0.289 | |
| lag 1 | 0.174 | -0.044 | 0.088 | 0.062 | -0.012 | -0.084 | -0.028 | 0.138 | |
| lag 2 | 0.106 | -0.114 | 0.033 | 0.019 | -0.114 | 0.009 | -0.022 | 0.066 | |
| | | <i>Ljung-Box Tests</i> | | | | | | | |
| Q statistic for lags 0 to 2 | 12.761 | 2.801 | 6.341 | 2.125 | 3.651 | 1.935 | 2.043 | 19.863 | |
| M-Signific | 0.01 | 0.42 | 0.10 | 0.55 | 0.30 | 0.59 | 0.56 | 0.00 | |
| Q statistic for lags 1 to 2 | 7.746 | 2.792 | 1.634 | 0.780 | 2.454 | 1.344 | 0.239 | 4.366 | |
| M-Signific | 0.02 | 0.25 | 0.44 | 0.68 | 0.29 | 0.51 | 0.89 | 0.11 | |
| B. Bank lending rate (i^L) | | <i>Correlation coefficients</i> | | | | | | | |
| lag 0 | 0.007 | 0.017 | 0.008 | -0.002 | -0.001 | -0.002 | 0.056 | 0.067 | |
| lag 1 | 0.007 | -0.002 | -0.010 | -0.022 | 0.008 | 0.008 | 0.004 | -0.007 | |
| lag 2 | 0.004 | 0.025 | 0.013 | -0.012 | 0.002 | 0.007 | 0.018 | 0.021 | |
| | | <i>Ljung-Box Tests</i> | | | | | | | |
| Q statistic for lags 0 to 2 | 0.021 | 0.177 | 0.060 | 0.116 | 0.012 | 0.020 | 0.651 | 0.927 | |
| M-Signific | 1.00 | 0.98 | 1.00 | 0.99 | 1.00 | 1.00 | 0.88 | 0.82 | |
| Q statistic for lags 1 to 2 | 0.012 | 0.121 | 0.048 | 0.116 | 0.012 | 0.019 | 0.064 | 0.090 | |
| M-Signific | 0.99 | 0.94 | 0.98 | 0.94 | 0.99 | 0.99 | 0.97 | 0.96 | |

Notes. Panels A and B report the cross correlations of bank lending (lagged) and bank lending rate (lagged) with the reduced-form residuals of the GZ model equations: $\rho(L_{-s}, e_j^{GZ})$ and $\rho(i_{-s}^L, e_j^{GZ})$ for lags $s = 0, 1, 2$ and equations $j = 1, 2, \dots, 8$. The Table also presents the results of two Ljung-Box tests for the null hypotheses of zero correlations between the banking variables and the residuals of each equation. For instance, in the case of bank lending, the Ljung-Box Q statistic for lags $M1$ to $M2$ is $Q = T(T+2) \sum_{M1 \leq s \leq M2} \frac{\rho(L_{-s}, e_j^{GZ})}{T-s}$. For a null hypothesis of no correlation at any lag, Q is asymptotically distributed as χ^2 with $M2 - M1 + 1$ degrees of freedom, and M-signific indicates the tests significance levels.

Table 2. Comparison of Forecast Performance of the Extended and GZ Models

Difference in RMSE of Forecasts from the Extended and GZ Models
(in percent of RMSE of the GZ model)

| Time horizon (quarters) | <i>Variable in the GZ model:</i> | | | | | | | |
|---|----------------------------------|-----------|-----------|-----------|------------|------------|-------------------------|------------------------|
| | <i>dC</i> | <i>dI</i> | <i>dY</i> | <i>dP</i> | <i>ebp</i> | <i>esr</i> | <i>i</i> ^{10y} | <i>i</i> ^{FF} |
| A. Bank lending growth (<i>dl</i>) | | | | | | | | |
| 1 | -22.9 | -15.2 | -11.2 | -9.8 | -15.3 | -13.1 | -11.6 | -22.7 |
| 2 | -15.2 | -11.0 | -14.5 | -10.8 | -19.7 | -14.2 | -17.7 | -31.5 |
| 3 | -13.8 | -11.6 | -12.5 | -13.7 | -22.0 | -11.3 | -22.1 | -40.6 |
| 4 | -13.4 | -11.0 | -9.9 | -16.6 | -21.5 | -7.0 | -27.9 | -43.1 |
| 8 | -11.8 | -0.9 | -2.5 | -31.8 | -38.3 | -10.5 | -39.6 | -51.3 |
| 12 | -16.6 | 4.4 | -6.5 | -39.2 | -10.8 | -11.4 | -46.1 | -51.9 |
| B. Bank lending rate (<i>i</i>^L) | | | | | | | | |
| 1 | -17.3 | -15.7 | -9.5 | -13.0 | -14.4 | -11.6 | -13.5 | -17.7 |
| 2 | -14.6 | -7.3 | -12.4 | -13.1 | -19.0 | -14.0 | -17.7 | -18.2 |
| 3 | -14.7 | -12.9 | -15.4 | -13.8 | -22.4 | -11.5 | -21.7 | -28.9 |
| 4 | -11.5 | -12.8 | -12.9 | -15.0 | -23.3 | -7.5 | -25.9 | -36.0 |
| 8 | -15.1 | -0.2 | -4.4 | -34.9 | -39.7 | -11.6 | -39.4 | -51.0 |
| 12 | -24.0 | 6.2 | -10.0 | -45.4 | -11.3 | -11.5 | -49.9 | -54.4 |
| C. Bank lending growth and lending rate (<i>dl, i</i>^L) | | | | | | | | |
| 1 | -21.7 | -14.9 | -11.1 | -12.9 | -15.2 | -13.2 | -13.1 | -16.5 |
| 2 | -16.0 | -8.1 | -14.6 | -13.0 | -19.5 | -14.5 | -18.0 | -19.2 |
| 3 | -14.5 | -13.3 | -15.2 | -13.8 | -22.1 | -12.2 | -21.9 | -30.0 |
| 4 | -13.0 | -12.1 | -11.9 | -14.1 | -22.1 | -7.7 | -26.9 | -34.8 |
| 8 | -11.4 | -0.8 | -1.7 | -33.0 | -37.1 | -11.1 | -40.9 | -48.5 |
| 12 | -18.4 | 5.1 | -6.3 | -44.4 | -10.6 | -11.7 | -51.0 | -54.3 |

Notes. The Table reports, for the indicated variables and equations j of the VAR model, the following:

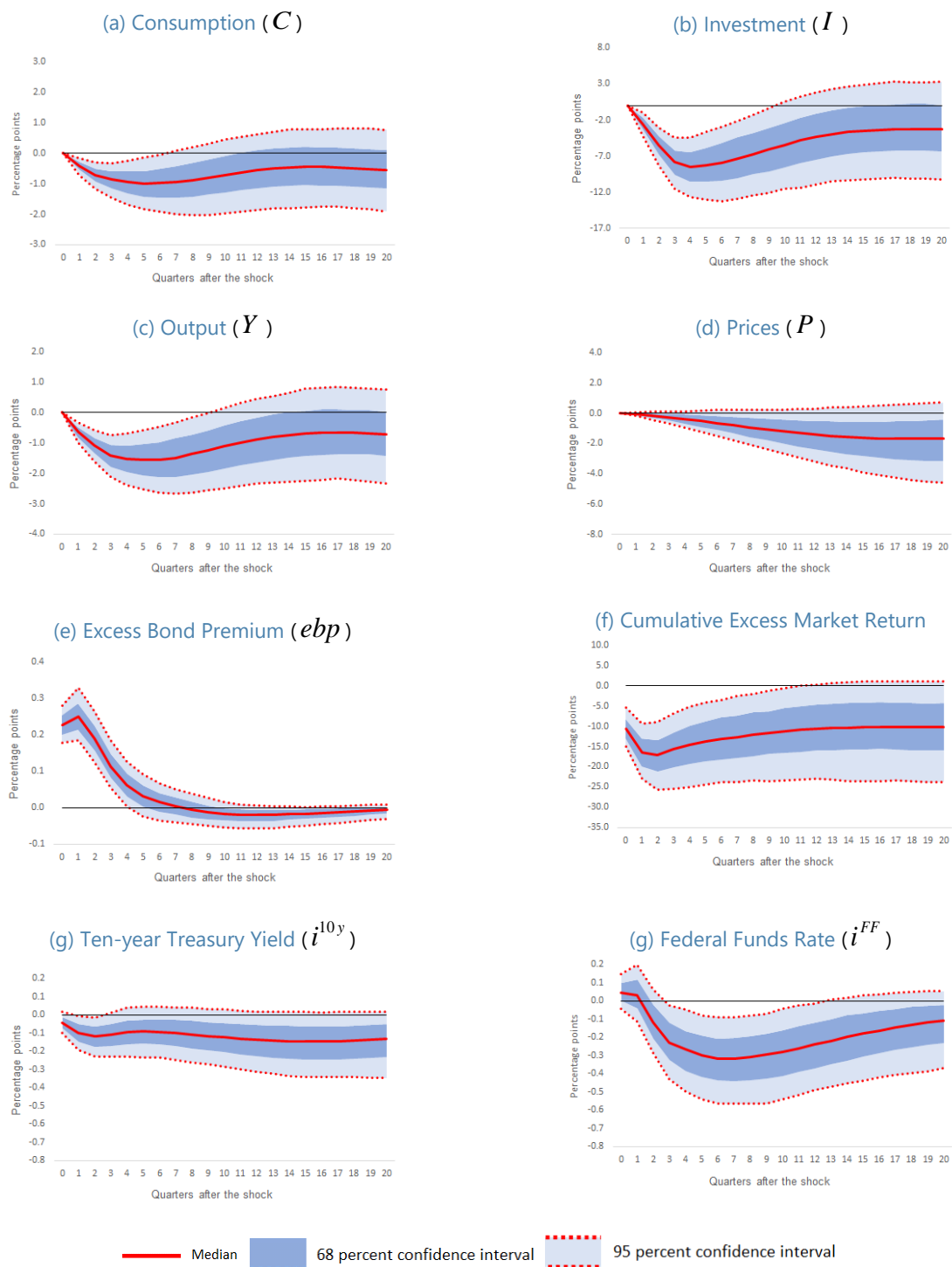
$\left[(RMSE_j / RMSE_j^{GZ}) - 1 \right] * 100$, where $RMSE_j$ and $RMSE_j^{GZ}$ denote the root mean square errors of out-of-sample forecasts generated with the extended and the GZ models, respectively. Out-of-sample forecasts start in 2008:Q1 and are generated using recursive regressions, with the initial estimation period spanning from 1972:Q4 to 2007:Q4.

Table 3. Tests for Omission of Banking Sector Variables in the GZ Model

| | dC | dI | dY | dP | ebp | esr | i^{10y} | i^{FF} | GZ Model (system-wide) | |
|---|-------|--------|--------|-------|-------|-------|-----------|----------|------------------------|----------|
| A. Bank lending growth (dl) | | | | | | | | | | |
| <i>Granger-Causality of bank lending for:</i> | | | | | | | | | | |
| Chi-squared (2) (lags 1 to 2) | 9.69 | 3.16 | 2.40 | 1.12 | 3.22 | 2.39 | 0.48 | 5.65 | Chi-squared (16) | 77.38 |
| M-Signific | 0.01 | 0.21 | 0.30 | 0.57 | 0.20 | 0.30 | 0.79 | 0.06 | M-Signific | 0.00 |
| <i>Sims-Exogeneity of bank lending with respect to:</i> | | | | | | | | | | |
| Chi-squared (2) (leads 1 to 2) | 0.25 | 3.84 | 1.96 | 4.80 | 2.60 | 2.56 | 4.11 | 2.27 | Chi-squared (16) | 25.98 |
| M-Signific | 0.88 | 0.15 | 0.37 | 0.09 | 0.27 | 0.28 | 0.13 | 0.32 | M-Signific | 0.05 |
| <i>Canova-Hamidi exogeneity test for bank lending with respect to the reduced form residuals of:</i> | | | | | | | | | | |
| Chi-squared (2) (leads 1 to 2) | 2.82 | 1.08 | 0.81 | 0.86 | 5.01 | 1.58 | 1.37 | 0.93 | Chi-squared (16) | 28.77 |
| M-Signific | 0.24 | 0.58 | 0.67 | 0.65 | 0.08 | 0.45 | 0.50 | 0.63 | M-Signific | 0.03 |
| <i>Forni-Gambetti orthogonality of ebp structural innovation from GZ model:</i> | | | | | | | | | | |
| Chi-squared (2) (lags 1 to 2) | | | | | 2.94 | | | | | |
| M-Signific | | | | | 0.23 | | | | | |
| B. Lending rate (i^L) | | | | | | | | | | |
| <i>Granger-Causality of lending rate for:</i> | | | | | | | | | | |
| Chi-squared (2) (lags 1 to 2) | 0.80 | 19.15 | 11.71 | 10.96 | 1.38 | 0.39 | 9.58 | 31.61 | Chi-squared (16) | 168.81 |
| M-Signific | 0.67 | 0.00 | 0.00 | 0.00 | 0.50 | 0.82 | 0.01 | 0.00 | M-Signific | 0.00 |
| <i>Sims-Exogeneity of lending rate with respect to:</i> | | | | | | | | | | |
| Chi-squared (2) (leads 1 to 2) | 9.85 | 22.32 | 16.12 | 2.20 | 1.20 | 1.33 | 0.80 | 38.97 | Chi-squared (16) | 63.14 |
| M-Signific | 0.01 | 0.00 | 0.00 | 0.33 | 0.55 | 0.52 | 0.67 | 0.00 | M-Signific | 0.00 |
| <i>Canova-Hamidi exogeneity test for lending rate with respect to the reduced form residuals of:</i> | | | | | | | | | | |
| Chi-squared (2) (leads 1 to 2) | 5.78 | 5.25 | 3.56 | 1.10 | 1.48 | 0.42 | 1.01 | 26.85 | Chi-squared (16) | 73.03 |
| M-Signific | 0.06 | 0.07 | 0.17 | 0.58 | 0.48 | 0.81 | 0.60 | 0.00 | M-Signific | 0.00 |
| <i>Forni-Gambetti orthogonality of ebp structural innovation from GZ model:</i> | | | | | | | | | | |
| Chi-squared (2) (lags 1 to 2) | | | | | 0.07 | | | | | |
| M-Signific | | | | | 0.97 | | | | | |
| C. Bank lending growth and lending rate (dl, i^L) | | | | | | | | | | |
| <i>Granger-Causality of bank lending and lending rate for:</i> | | | | | | | | | | |
| Chi-squared (2) (lags 1 to 2) | 10.48 | 22.60 | 12.94 | 11.10 | 4.67 | 2.44 | 10.76 | 35.83 | Chi-squared (32) | 256.60 |
| M-Signific | 0.03 | 0.00 | 0.01 | 0.03 | 0.32 | 0.66 | 0.03 | 0.00 | M-Signific | 0.00 |
| <i>Sims-Exogeneity of bank lending and lending rate with respect to:</i> | | | | | | | | | | |
| Chi-squared (2) (leads 1 to 2) | 67.62 | 161.74 | 109.67 | 39.81 | 32.76 | 24.03 | 40.45 | 975.74 | Chi-squared (32) | 7,677.92 |
| M-Signific | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | M-Signific | 0.00 |
| <i>Canova-Hamidi exogeneity test for bank lending and lending rate with respect to the reduced form residuals of:</i> | | | | | | | | | | |
| Chi-squared (2) (leads 1 to 2) | 73.92 | 36.71 | 30.71 | 15.16 | 44.56 | 10.89 | 20.82 | 289.43 | Chi-squared (32) | 3,479.18 |
| M-Signific | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 | M-Signific | 0.00 |
| <i>Forni-Gambetti orthogonality of ebp structural innovation from GZ model:</i> | | | | | | | | | | |
| Chi-squared (2) (lags 1 to 2) | | | | | 2.91 | | | | | |
| M-Signific | | | | | 0.57 | | | | | |

Notes. See Appendix II for further details on the implementation of the tests presented in this Table.

Figure 1. Impulse Responses on Non-banking Variables to an Excess Bond Premium Shock in the Extended Model



Notes. The Figure shows IRFs to a one standard deviation structural ebp shock. The extended model includes bank lending and the lending rate and is estimated using data for the “full” sample period (1972:Q4-2019:Q4). The shaded bands denote the 68 and 95 percent bias-corrected confidence intervals for impulse responses corresponding to the extended model. The confidence intervals were constructed using the “bootstrap-after-bootstrap” approach of Kilian (1998) with 2,000 bootstrap replications.

Figure 2. Impulse Responses of Bank Lending and Lending Rate to an Excess Bond Premium Shock in the Extended Model

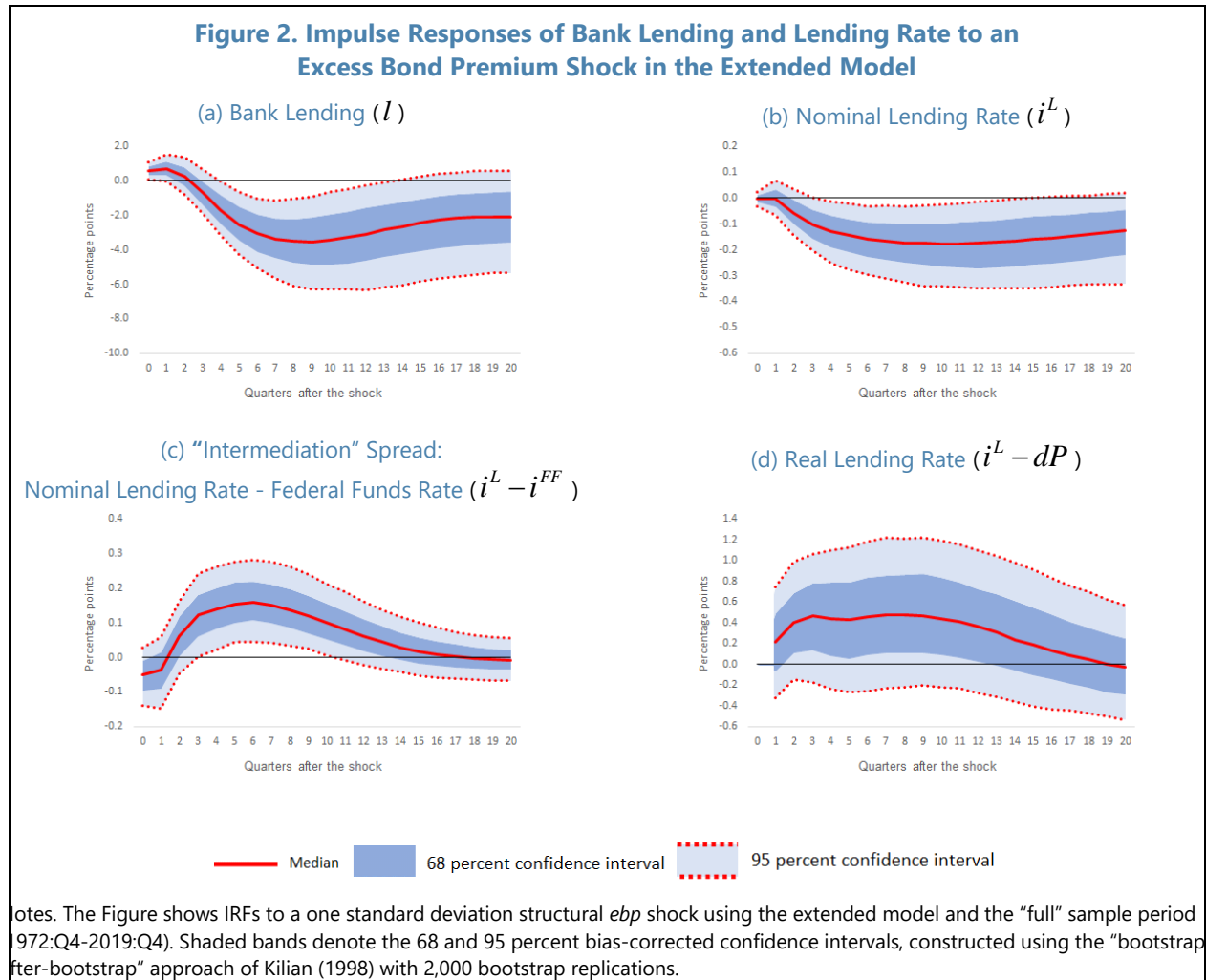
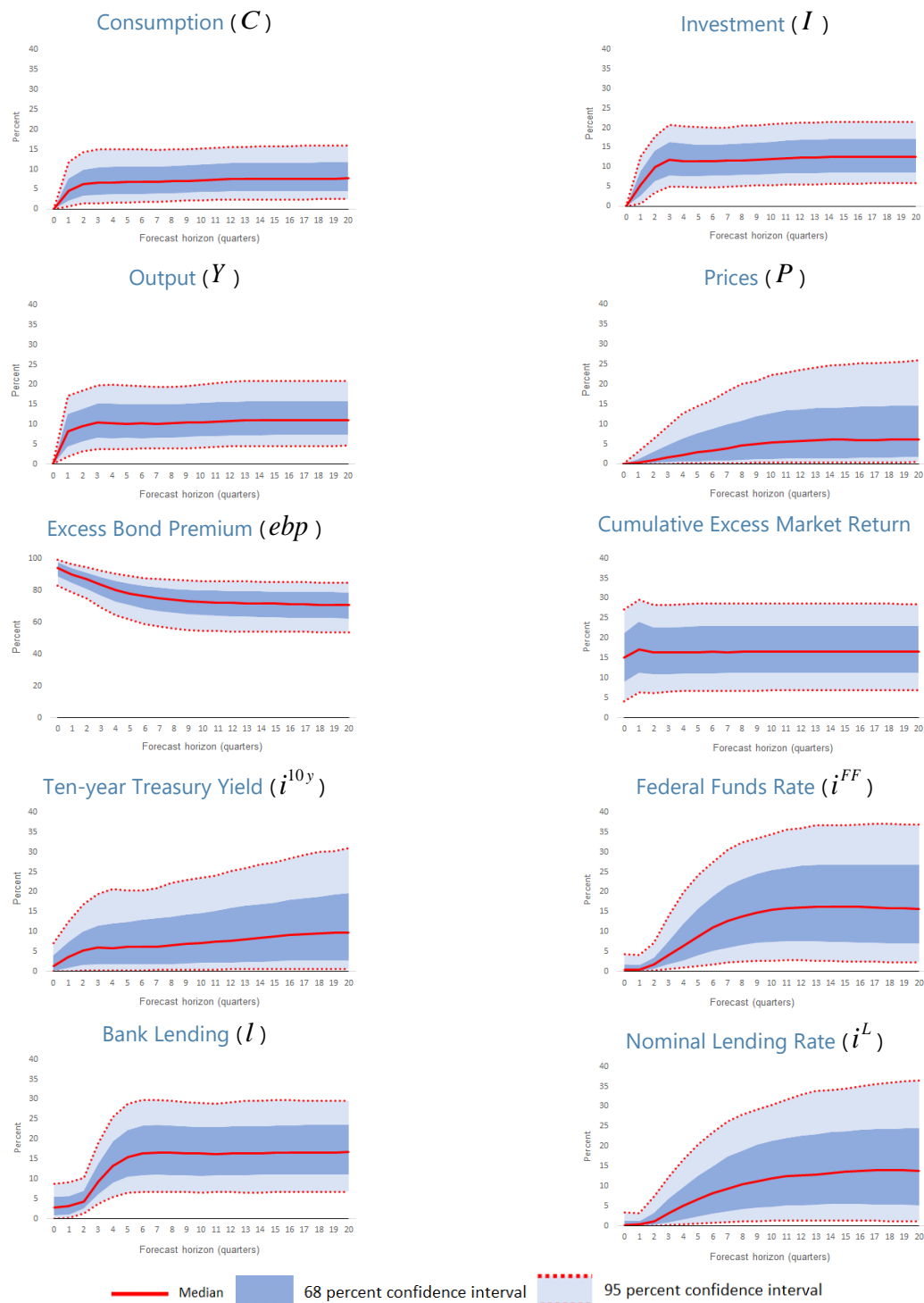
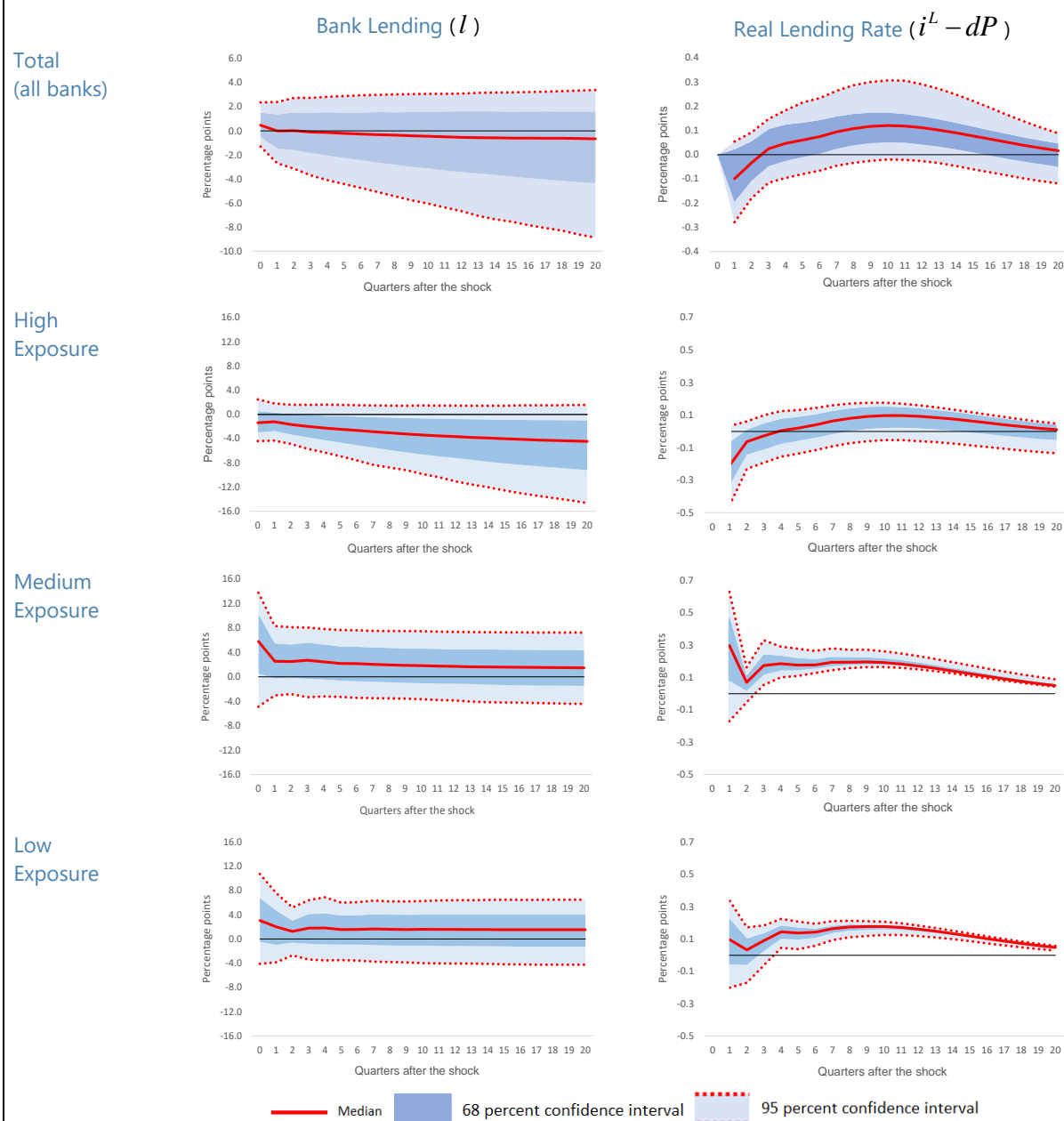


Figure 3. Forecast Error Variance Decomposition of an Excess Bond Premium Shock
(based on the extended model)



Notes. The Figure shows variance decompositions for the extended model using the “full” sample period (1972:Q4-2019:Q4). Shaded bands denote the 68 and 95 percent bias-corrected confidence intervals, constructed using the “bootstrap-after-bootstrap” approach of Kilian (1998) with 2,000 bootstrap replications.

Figure 4. Dynamic Responses of Bank lending and Real Lending Rate to an Excess Bond Premium Shock for Banks with Different Degrees of Exposure to the Corporate Bond Market



Notes. The Figure shows the dynamic responses of banks with high, medium, and low exposure to the corporate bond market, obtained from three near-VAR models estimated using the sample period from 2002:Q1 to 2019:Q4. Shaded bands denote the 68 and 95 percent bias-corrected confidence intervals, constructed using the "bootstrap-after-bootstrap" approach of Kilian (1998), with 1,000 replications to compute the bias followed by 2,000 replications to compute the confidence bands.

APPENDIX I: DATA SOURCES AND TRANSFORMATIONS

a. Aggregate macro-financial data

| Series | Transformation | Unit | Source | Database Mnemonic |
|-------------------------------|---|---|---|---|
| Consumption growth | Change in the log level | Percent, annualized | U.S. Bureau of Economic Analysis, Real Personal Consumption Expenditure from FRED | PCECC96 |
| Investment growth | Change in the log level | Percent, annualized | U.S. Bureau of Economic Analysis, Real Gross Private Domestic Investment from FRED | GPDIC1 |
| GDP growth | Change in the log level | Percent, annualized | U.S. Bureau of Economic Analysis, Real Gross Domestic Product from FRED | GDPIC1 |
| Inflation | Change in the log level | Percent, annualized | U.S. Bureau of Economic Analysis, Gross Domestic Product: Implicit Price Deflator from FRED | A191R11Q225SBEA |
| Excess bond premium | None | Percent, annualized | Gilchrist and Zakrajšek. 2012. Updated series available at: https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv | EBP |
| Treasury bill rate (3 months) | None | Annual rate (discount basis) in percent, first day in the quarter | Board of Governors of the Federal Reserve System (US), 3-Month Treasury Bill Secondary Market Rate, Discount Basis from FRED | DTB3 |
| S&P 500 total return index | None | Index | Global Financial Data | S&P 500 Total Return Index (w/GFD extension) |
| Excess stock market return | Percentage change of snp500 (quarter on quarter, eop) annualized minus Treasury bill rate (3 months) | Annual rate in percent | Authors' calculations | N.A. |
| Federal funds rate | Average of monthly series | Annual rate in percent | Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate from FRED | FEDFUNDS |
| Bank lending growth | Change in the log level | Percent, annualized | Loans and leases and other securities from Federal Reserve Board (FRB_H8) deflated using the GDP Implicit Price Deflator from the U.S. Bureau of Economic Analysis | FRB_H8: Loans and leases (B1020NCBA) and other securities (B1011NCBA) |
| Finance rate new autos | Average of monthly series | Annual rate in percent | Board of Governors of the Federal Reserve System (US), Finance Rate on Consumer Installment Loans at Commercial Banks, New Autos 48 Month Loan from FRED | TERMCBAUTO48NS |
| 30-year fixed rate mortgage | Average of monthly series | Annual rate in percent | Freddie Mac, 30-Year Fixed Rate Mortgage Average in the United States from FRED. | MORTGAGE30US |
| Finance rate personal loans | Average of monthly series | Annual rate in percent | Board of Governors of the Federal Reserve System (US), Finance Rate on Personal Loans at Commercial Banks, 24 Month Loan from FRED | TERMCBPER24NS |
| Prime rate | Average of monthly series | Annual rate in percent | Board of Governors of the Federal Reserve System (US), Bank Prime Loan Rate from FRED | MPRIME |
| Lending rate | First principal component of: (i) Finance rate new autos, (ii) 30-year fixed rate mortgage, and (iii) Prime rate. | Annual rate in percent | Authors' calculations | N.A. |

b. Microdata from Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices (Call Reports)

| Series | Transformation | Unit | Source | Database Mnemonic |
|---|--|-----------------------------|--|--------------------------|
| Total liabilities | None | Dollar amounts in thousands | Call Reports: Schedule RC-Balance Sheet (Form Type-031), item 21 | RCFD2948 |
| Deposits | None | Dollar amounts in thousands | Call Reports: Schedule RC-Balance Sheet (Form Type-031), items 13a and 13b | RCORCON2200 + RCFN2200 |
| Non-deposit debt funding to total debt funding ratio | (Total liabilities - Deposits) / Total liabilities | Percent | Author's calculations | N.A. |
| Gross loans | None | Dollar amounts in thousands | Call Reports: Schedule RC-Balance Sheet (Form Type-031), Loans and lease financing receivables, items 4a and 4b | RCFD5369 + RCFDB528 |
| Bank lending growth | Change in the log level | Percent, annualized | Gross loans deflated using the GDP Implicit Price Deflator from the U.S. Bureau of Economic Analysis | N.A. |
| Interest income | None | Dollar amounts in thousands | Call Reports: Schedule RI-Income Statement (Form Type-031), Total interest and fee income on loans, items 1.a.3, and Income from lease finance receivables, item 1.b | RIAD4010 + RIAD4065 |
| Lending rate | Interest income (period t) / Gross loans (end of period t-1) | Annual rate in percent | See above for the sources of interest income and gross loans | N.A. |

APPENDIX II: OMISSION AND FUNDAMENTALNESS TESTS

Table A1. Omission Tests

Equation by equation tests

$$(i = 1, 2, \dots, 8)$$

System-wide tests

Granger Causality

Individual banking variables:

$$y_{i,t}^{GZ} = \mathbf{a}(L) \cdot \mathbf{y}_t^{GZ} + b_x(L) \cdot x_t + v_{i,t},$$

where $x \in \{1, i^1\}$, $\mathbf{a}(L)$ is a (row) vector of lag polynomials of order 2, $b_x(L)$ is a lag polynomial of order 2, and $v_{i,t}$ is an error term. Chi-squared test of $b_x(L) = 0$.

Both banking variables:

$$y_{i,t}^{GZ} = \mathbf{a}(L) \cdot \mathbf{y}_t^{GZ} + \mathbf{b}(L) \cdot \mathbf{y}_t^b + v_{i,t},$$

where $\mathbf{a}(L)$ is a (row) vector of lag polynomials of order 2 and $\mathbf{b}(L) = [b_1(L) \quad b_i(L)]$. Chi-squared test of $\mathbf{b}(L) = \mathbf{0}$.

Individual banking variables:

$$\mathbf{y}_t^{GZ} = \mathbf{A}^{GZ}(L) \cdot \mathbf{y}_t^{GZ} + \mathbf{b}_x(L) \cdot x_t + \mathbf{v}_t$$

where $x \in \{1, i^1\}$, $\mathbf{A}^{GZ}(L)$ is a matrix of lag polynomials of order 2, $\mathbf{b}_x(L)$ is a (column) vector of lag polynomial of order 2, and \mathbf{v}_t is a vector of error terms. Chi-squared test of $\mathbf{b}_x(L) = \mathbf{0}$.

Both banking variables:

$$\mathbf{y}_t^{GZ} = \mathbf{A}^{GZ}(L) \cdot \mathbf{y}_t^{GZ} + \mathbf{B}(L) \cdot \mathbf{y}_t^b + \mathbf{v}_t$$

where $\mathbf{A}^{GZ}(L)$ and $\mathbf{B}(L)$ are matrices of lag polynomials of order 2. Chi-squared test of $\mathbf{B}(L) = \mathbf{0}$.

Sims Exogeneity

Individual banking variables:

$$x_t = b_x(L) \cdot x_t + c(L) \cdot y_{i,t}^{GZ} + v_t,$$

where $x \in \{1, i^1\}$, $b_x(L)$ is a lag polynomial of order 2, and $c(L)$ is a two-sided lag polynomial of order 2. Chi-squared test of the leads in $c(L) = 0$.

Both banking variables:

$$\mathbf{y}_t^b = \mathbf{B}(L) \cdot \mathbf{y}_t^b + \mathbf{c}(L) \cdot \mathbf{y}_t^{GZ} + \mathbf{v}_t,$$

where $\mathbf{B}(L)$ is a matrix of lag polynomials of order 2 and $\mathbf{c}(L)$ is a (column) vector of two-sided lag polynomials of order 2. Chi-squared test of the leads in $\mathbf{c}(L) = \mathbf{0}$.

Individual banking variables:

$$x_t = b_x(L) \cdot x_t + \mathbf{c}(L) \cdot \mathbf{y}_t^{GZ} + v_t$$

where $x \in \{1, i^1\}$, $b_x(L)$ is a lag polynomial of order 2, and $\mathbf{c}(L)$ is a (row) vector of two-sided lag polynomials of order 2. Chi-squared test of the leads in $\mathbf{c}(L) = \mathbf{0}$.

Both banking variables:

$$\mathbf{y}_t^b = \mathbf{B}(L) \cdot \mathbf{y}_t^b + \mathbf{C}(L) \cdot \mathbf{y}_t^{GZ} + \mathbf{v}_t,$$

where $\mathbf{B}(L)$ is a matrix of lag polynomials of order 2 and $\mathbf{C}(L)$ is a matrix of two-sided lag polynomials of order 2. Chi-squared test of the leads in $\mathbf{C}(L) = \mathbf{0}$.

Notes. Note. All Chi-squared tests are performed as Wald tests. The equation-by-equation test statistics takes a standard (excluded variables) F-statistic and multiplies it by the degrees of freedom in the numerator (see Theorem 5.1, page 135, Green eighth edition, 2018); an analogous calculation is performed for system-wide tests. The Sims exogeneity tests include lagged dependent variables; that is, we report the Geweke, Messe and Dent (1983) version of the Sims test.

Table A2. Fundamentalness Tests

Equation by equation tests

 $(i = 1, 2, \dots, 8)$

Canova-Hamidi Sahneh

Individual banking variables:

$$x_t = b_x(L) \cdot x_t + d(L) \cdot e_{i,t}^{GZ} + v_t,$$

where $x \in \{1, i^1\}$, $e_{i,t}^{GZ}$ are the reduced form residuals from equation i in the GZ VAR, $b_x(L)$ is a lag polynomial of order 2, and $d(L)$ is a two-sided lag polynomial of order 2. Chi-squared test of the leads in $d(L) = \mathbf{0}$.

Both banking variables:

$$y_t^b = \mathbf{B}(L) \cdot y_t^b + \mathbf{d}(L) \cdot e_{i,t}^{GZ} + v_t,$$

where $e_{i,t}^{GZ}$ are reduced form residuals from equation i in the GZ VAR, $\mathbf{B}(L)$ is a matrix of lag polynomials of order 2 and $\mathbf{d}(L)$ is a (column) vector of two-sided lag polynomials of order 2. Chi-squared test of the leads in $\mathbf{d}(L) = \mathbf{0}$.

Forni-Gambetti

Individual banking variables:

$$\varepsilon_{5,t}^{GZ} = G(L) \cdot \varepsilon_{5,t}^{GZ} + b_x(L) \cdot x_t + v_t,$$

where $x \in \{1, i^1\}$, $\varepsilon_{5,t}^{GZ}$ are structural innovations to the excess bond premium (ebp) in the GZ VAR, and $G(L)$ and $b_x(L)$ are lag polynomials of order 2. Chi-squared test of $b_x(L) = \mathbf{0}$.

Both banking variables:

$$\varepsilon_{5,t}^{GZ} = G(L) \cdot \varepsilon_{5,t}^{GZ} + \mathbf{b}(L) \cdot y_t^b + v_t,$$

where $\varepsilon_{5,t}^{GZ}$ are structural innovations to the excess bond premium (ebp) in the GZ VAR, $G(L)$ is a lag polynomial of order 2, and $\mathbf{b}(L) = \begin{bmatrix} b_1(L) & b_i(L) \end{bmatrix}$. Chi-squared test of $\mathbf{b}(L) = \mathbf{0}$.

Notes. All Chi-squared tests are performed as Wald tests. The equation-by-equation test statistics takes a standard (excluded variables) F-statistic and multiplies it by the degrees of freedom in the numerator; an analogous calculation is performed for system-wide tests. The Canova-Hamidi tests include lagged dependent variables (see Forni, Gambetti, and Sala (2018)), as in the Geweke, Messe and Dent (1983) version of the Sims test.

System-wide tests

Individual banking variables:

$$x_t = b_x(L) \cdot x_t + \mathbf{d}(L) \cdot \mathbf{e}_t^{GZ} + v_t$$

where $x \in \{1, i^1\}$, \mathbf{e}_t^{GZ} is the vector of reduced form residuals of the GZ VAR, $b_x(L)$ is a lag polynomial of order 2, and $\mathbf{d}(L)$ is a (row) vector of two-sided lag polynomials of order 2. Chi-squared test of the leads in $\mathbf{d}(L) = \mathbf{0}$.

Both banking variables:

$$y_t^b = \mathbf{B}(L) \cdot y_t^b + \mathbf{D}(L) \cdot \mathbf{e}_t^{GZ} + v_t,$$

where \mathbf{e}_t^{GZ} is the vector of reduced form residuals of the GZ VAR, $\mathbf{B}(L)$ is a matrix of lag polynomials of order 2 and $\mathbf{D}(L)$ is a matrix of two-sided lag polynomials of order 2. Chi-squared test of the leads in $\mathbf{D}(L) = \mathbf{0}$.

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