Banks Strategies and Credit Spreads as Leading Indicators for the Real Business Cycles Fluctuations

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Abstract

Following Gilchrist and Zakrajsek (2012), we decompose bond credit spreads into a component that reflects the probability of default of the corporate firm and a residual referred to as "excess bond premium" (henceforth *EBP*). The latter appears to be a leading indicator of real business cycles. Our main contribution is in providing empirical support to the hypothesis that the *EBP* in part reflect the influence of the commercial banks' strategies on corporate bond pricing. This influence emanates from the *superiority* of information on firms' debt repayment and settlement banks have and capital market lenders do not. This superiority comes about from the relatively high monitoring costs and the constrained restructuring ability capital market lenders face. These findings are consistent with the notion that a rise in *EBP* reflects a measure taken by banks that could lead to further downturns in the economy.

Key words: *Bond credit spreads; Distance to default; Excess bond premium; Banking loan loss reserves; Banking capital ratio; banking coverage ratio*. *Business cycles*.

JEL classification: E32, G12, G14, G21.

תקציר

מחקר זה בוחן את ההתנהגות הדינמית של הפער בין התשואות על אג"ח קונצרניות לבין התשואות על אג"ח ממשלתיות, וזאת באמצעות פירוק הפער למרכיב שמבטא את פרמיית הסיכון לפשיטת רגל של הפירמה המנפיקה ולשארית שמבטאת את התשואה העודפת בתמחור האג"ח – Excess Bond Premium, EBP. המחקר מתבסס על ניתוח שערכו Gilchrist and Zakrajsek (2012) לגבי המשק האמריקאי, והוא מוצא כי בדומה למצב בארה"ב, גם בישראל ה-EBP הוא משתנה מוביל למחזורי העסקים הריאליים. הממצא העיקרי הוא שהדינמיקה של ה-EBP מושפעת מאסטרטגיות עסקיות שמאמצים הבנקים בניהול השוטף של עסקיהם ובעיקר של מדיניות הסיכונים. יוצא אפוא שהבנקים משפיעים על מחזורי העסקים הריאליים דרך השפעתם על תמחור האג"ח בשוק ההון. השפעה זו נובעת מכך שאין סימטריה בין הבנקים למלווים משוק ההון, שכן יחסית לאחרונים הבנקים יכולים לעקוב אחר לקוחותיהם בעלויות נמוכות, לעזור ללקוחותיהם להתמודד עם התחייבויותיהם הפיננסיות, ולנצל יתרונות לגודל במדיניות הסיכונים.

1. Introduction

At the beginning of the recent global financial crisis, economies around the globe suffered severe liquidity shortages and a credit crunch, probably the worst since the Great Depression. Since this recent crisis monetary policymakers and monetary economics researchers have been paying much more attention and giving much more consideration to the functioning of the monetary policy transmission mechanism, that is, the channel from the monetary policy key rate to interest rates in the financial market and through it to investors, savers and other economic agents.

In line with this development, Gilchrist and Zakrajsek (2012) (henceforth GZ) consider the yield spread (henceforth "credit spreads") in the bond market as part of the monetary transmission mechanism to argue that "… credit spreads—the difference in yields between various private debt instruments and government securities of comparable maturity—served as a crucial gauge of the degree of strains in the financial system…. In addition, movements in credit spreads were thought to contain important signals regarding the evolution of the real economy…". (GZ)

Elton et al. (2001), in explaining the credit spreads, distinguish between (i) the effect of the expected default loss on the credit spread; (ii) the effect of the tax treatment of corporate bonds; and (iii) the effect of the credit risk premium. Consistently with this decomposition, they find empirical support in the US data for these effects. Similarly GZ decompose the credit spreads into two components. The first is a component that captures the countercyclical movements in expected default of the corporate bond issuer. This component reflects the available firm-specific information on the borrowing firm's financial health and is by definition correlated with a measure of the probability of default loss of the corporate debt issuer. The second component, which GZ termed an *excessive bond premium* (henceforth *EBP*), is an unexplained portion of the variation in the credit spreads that reflects (capital markets and banks) lenders preferences towards risk and risk management strategies. More precisely it is a default-risk factor that captures compensation for bearing exposure to corporate firm's credit risk, required by lenders above and beyond the expected default loss.[1]

In that respect GZ argue that "This decomposition is motivated in part by the existence of the 'credit spread puzzle,' the well-known result from the corporate finance literature, showing that less than one-half of the variation in corporate bond credit spreads can be attributed to the financial health of the issuer,...". *GZ* use US data on the financial health of the corporate borrowing firms, and apply Merton (1974) to compute the borrower's distance to default (henceforth *DD*) - an index for the repayment ability of the borrowing firm. Note that *GZ* do not directly compute the *EBP* based on a conceptual framework, but rather derive it empirically as a *residual* component. The *EBP* is hence by construction orthogonal to the *DD*.

Both components of the credit spreads were found by *GZ* to have certain characteristics, including being leading indicators (having predictive power) of the real economic fluctuations. Furthermore, they find that the *EBP* has a significantly larger influence on the real business cycles than the other component of the credit spread. These results indicate that a substantial portion of the informative content of the *GZ* credit spread is originated in the deviation of the pricing of the corporate bonds from the measure of the expected default loss. Our contribution is in providing theoretical and empirical analysis of the *EBP* dynamics, in particular we show that banking strategies affect the capital spreads in a way that is predictable and statistically

[1] According to *GZ,* variations in this default-risk factor could originate in changes in the lender's attitude toward risk, but they did not pursue this line of research.

testable. The motivation to examine the influence of bank's strategies on the capital market pricing comes from the structural asymmetry of information between banks and capital market lenders.

Our view is that when there are frictions in the financial markets in the form of information asymmetry between lenders and borrowers and between lenders of different types (banks vs. capital market lenders) the effect of the credit risk premium (the aforementioned last component) on the credit spreads is more pronounced. (A discussion of the role of these frictions in pricing of the corporate bonds appears in the next section.) Consistently with this view, we examine and test whether the *EBP* is influenced by the *financial intermediary's strategies*. This is the main contribution of our research.

The financial intermediary's strategies can be reflected in changes in the availability of banking supply of funds or in changes in their risk management. These changes are hypothetically correlated with the real business cycles. Since by construction the *EBP* is orthogonal to the *DD*, anything that is found significantly influencing the *EBP* is expected to be orthogonal to the *DD*. In order to test this hypothesis we empirically identify banking strategies as well as the informative content of the credit spreads in an environment that shies away from the frictionless financial markets of Modigliani and Miller.

In this environment financial intermediaries play a central role in the linkages between the quality of the borrowers and their access to external finance. By activating measures like monitoring borrowers, exploiting economies to scale in their risk managements, applying credit rationing strategy and the like, they (the banks) can in fact mitigate the effects of the information asymmetry. This analysis integrates into the literature that shows that financial intermediation and debt contracts help in ameliorating the economic consequences of information asymmetry with beneficial implications for resource allocation and economic activity (see Townsend (1979); Diamond and Dybvig (1983); Diamond (1984); Gale and Hellwig (1985); Boyd and Prescott (1986); and Beck et al. (2000) to mention few).

Bleaney et al. (2012) apply GZ's methodology utilizing European bond markets, and find similar results regarding the influence of the *EBP* on the real business cycles. Gilchrist & Mojon (2014) also study the informative content of the bond yield spreads for different sectors (including the financial sectors) in the Eurozone. They also found the credit spreads to be robust leading indicators for the real business cycles. In line with this literature, Sasi-Brodesky (2013) also uses Merton (1974) to calculate the probability of default of corporate firms utilizing Israeli data and examines whether the credit spreads in the capital market are large enough to compensate lenders for the corporate firm's probability of default. In line with *GZ* she finds that there is excessive bond premium.

For the empirical application we use a panel of micro-level Israeli data from the capital markets including, among others, yields on corporate bonds and on government bonds; other financial characteristics of the corporate firms; and financial data on the Israeli banking system. To empirically identify the banks' strategies we use special US and Israeli data (specified later).[2] Our main finding is the empirical support for the hypothesis regarding the influence of the banks' strategies on the *EBP*. In the application of the GZ methodology using Israeli capital market data we find that the *EBP* components of the credit spreads in the Israeli capital market are leading indicators for the real business cycles as was found in the US and in Europe. Our study integrates also into the literature that describes the link between the banking

[2] Unfortunately, the length of the available Israeli data series is significantly smaller than that of the US, hence limiting our statistical analysis.

system and macroeconomic activity (see, for example, Monnin and Jokipii (2010)), but in our paper this relationship transpires through bond market pricing.

The paper is organized as follows. Following the introduction, we provide a brief conceptual framework that mainly deals with the role of the assumed information asymmetry. In section 3 the credit spreads are constructed and then followed by the study of their effects on the real business cycles. The decomposition of the credit spreads is done in section 4, utilizing the Merton (1974) index for the computation of the probability of default of Israeli corporate firms. The next section explores the extent to which the two decomposed components of the credit spreads maintain the property of being leading indicators of the real business cycles. In Section 6 we identify the effects of the Israeli commercial banks' strategies on the excess bond premium, and in section 7 we conclude. Most of the technical work, in which we simply follow GZ in their treatment of the credit spreads, appears in appendices A–D.

2. Conceptual Framework

As we alluded to in the introduction, the hypothesized relationship between the banking strategies and the *EBP,* if exists, may have originated in the financial market friction in the form of information asymmetry. The conceptual framework within which this relationship emerges consists of information known to certain players while others rely on signals in order to appropriately price their assets and/or liabilities. Conceptually, under the efficient market hypothesis, the borrowers' and lenders' information that is relevant and known in the capital markets should be correlated with the borrower's probability of default, and thus by construction be orthogonal to the *EBP*. However, since we assume there are frictions in the capital markets, some exclusive information known to banks triggers the use of the banks' specific strategies that send signals to the capital markets. This signaling eventually influences the pricing in these markets and thus its effect may appear in the *EBP*.

We assume there are two kinds of financial market frictions in the model environment. The first includes frictions that stem from the costly state verification characteristics that give rise to superior information regarding their net worth that borrowers have over financial intermediaries (banks) and other capital market lenders. The second type includes frictions that come about due to the *inferiority* of information on firms' debt repayment and settlement that is available in the capital markets as compared with the information known to banks. This latter kind of information asymmetry emerges due to the relatively high monitoring costs and the constrained restructuring ability capital market lenders face. For lenders to evaluate the required premium, they need to identify the shock that makes the information asymmetry relevant and assess its influence on both lenders and borrowers. The decomposition of the credit spreads, as is done in *GZ,* enables us to track the influence of the shocks on the pricing of bonds including that of the *EBP*.

Financial market frictions prevent financial institutions and other lenders from appropriately pricing their extended loans. Instead, these institutions (mainly banks) resort to various policy strategies[3] including restructuring their borrower debts, credit rationing, monitoring, required collaterals, holding financial capital, employing risk management experts, the accumulation of loan loss reserves and so forth. These measures are considered within the framework of banks' prudential risk management and, once activated, may have bearings on capital market equilibrium pricing.

The dynamics that is generated by the frictions works as follows. In the case of the costly state verification a shock to the net worth cannot be identified and

[3] Banks can usually resort to a wider range of tools and constraints than other lenders.

thereby be evaluated in the probability of default of the borrower firm, and can only trigger the aforementioned measures to be undertaken by banks and possibly by some other lenders. These measures either influence capital market equilibrium directly by shifting borrowers away from or to banks, or deliver signals to capital market participants which they take into consideration in pricing the bonds. Consequently in these cases due to the frictions, the pricing of the corporate bonds will be done by adjusting the *EBP*.

In the case of the capital markets' inferior information (relative to banks) on the borrowers' financial health, the measures employed by the banks in reaction to a financial shock may drive their own clientele and others into or out of the capital market. Because of this inferiority capital market lenders cannot differentiate between borrowers' financial health and consequently resort to indiscriminative pricing through the *EBP*. These frictions are therefore instrumental in generating the influence of these banking policy strategies on the *EBP*. Bryant (1980) demonstrates explicitly how banks’ strategies send relevant signals to the capital markets, which influence the pricing in those markets.

3. Corporate Bond Credit Spread Index

We follow GZ’s methodology in constructing corporate bond credit spread indices, adopting their "bottom-up" approach (see Gilchrist, Yankov, and Zakrajsek (2009)) to have an index with high informative content for future economic developments. A micro-level sample of Israeli nonfinancial firms[4] is utilized for this study. The sample includes information on 688 firms over the 2003–2011 period, totaling 23,606 observations. For each firm in the sample we obtained its average monthly bond market value, duration, maturity at issue and credit rating of its daily issues during the

[4] Excluding financial corporate firms, but construction and holding companies are included.

month and other available information (summarized in Table 1).[5] To avoid duration mismatch in the computation of the credit spreads, we match each corporate bond with a zero-coupon government bond with similar duration and with similar present value of its cash flow.[6] Similar to GZ we define the credit spread by the difference between the corporate bond's yield and its government counterpart. For the computation of the credit spreads we used micro-level daily data. [7]

(Insert Table 1)

To ensure that our results are not driven by a small number of extreme observations, we filter out all observations for which the spread was negative or greater than 50, as well as observations in which the debt values are not strictly positive. The market values of the corporate firm's debt were all in constant prices. The final (filtered) sample includes 16,535 credit spreads of CPI-indexed bonds and 1,967 of unindexed bonds.

For time series analysis we also derive month t aggregate (over all firms) credit spreads, CS_t, where, following GZ, we apply the arithmetic average methodology in which the spread is calculated as $CS_t = \frac{1}{N_t}\sum_i \sum_k \sum_s CS_{ikst}$ at each month t, where N_t is the number of bonds outstanding in our sample and CS_{ikst} is the credit spread of corporate bond k (relative to a government bond with similar characteristics) of firm i on day s of month t. In Figure 1, we depict the dynamics of the CS_t along with two other frequently used types of spreads over the 2003–2011

[5] Unlike GZ, due to the small size of the Israeli capital market, we couldn't filter out issues to have only senior, unsecured ones with a fixed coupon schedule. However, we did take into account in our statistical methodology a tradability measure of the corporate bond, which to some extent indicates the firm's capital structure (see later in the text).

[6] For the computation of the present value we use the one-year government yield.

[7] To aggregate the daily credit spread into monthly frequency we followed two steps: first, for each corporate firm we take a weighted average of the credit spreads of all of its bond series traded in that day. In the second step we simply use the monthly average of all of the daily credit spreads of each corporate firm traded in that month. For each corporate firm the weights were the daily share of the market values of the bond's obligation in its total bonds' obligation traded on that day.

period. The other two types of credit spreads are the average yield differences between *BBB*-rated corporate bonds and *AA*-rated corporate bonds, and the yield spread between business sector bonds with durations ranging for 0.5–2 years and government bonds with similar durations. The shaded area indicates periods of recession.

Apparently all of these three credit spreads widened during recessions, indicating a higher risk premium and counter-cyclicality (see Figure 1). Furthermore, all three started to rise about 6 quarters before the OECD identification of the beginning of the 2008–2009 recession.

(Insert Figure 1)

Next we analyze the relationship between credit spreads and current economic activity and whether the credit spread is a leading indicator of fluctuations in the real business cycle. To that end, and in the spirit of *GZ*, we estimate the following equation:

$$dY_t = \alpha + \beta dY_{t-1} + \gamma CS_{t-1} + \lambda RB_{t-2} + \phi Z_t + \varepsilon_t \qquad (1)$$

where Y_t denotes the level of real activity and $dY_t = \ln(Y_t / Y_{t-1})$; *CS* denotes the credit spreads; *RB* is the real short-run interest; Z_t is a vector of exogenous control variables; and ε_t is the forecast error. In addition we use the aforementioned alternative measure for our *CS*. (For more details of the analysis and estimation results see Appendix *A*).

The bottom line that comes up in this analysis is that, similar to *GZ,* we found the credit spreads to be leading indicators of fluctuations in the real business cycles. That is, there is informative content in the credit spreads that helps in forecasting real activity. In what follows, we study this informative content and particularly its relationship with the financial intermediaries.[8]

4. Predicted Credit Spread and Excess Bond Premium

To further explore the informative content embedded in the credit spreads, we follow *GZ* in decomposing the credit spread *CS* into two parts: a component that captures the premium required by capital market lenders as compensation for the expected probability of default of the corporate issuer firm; and the residual *EBP*. In line with our conceptual framework we argue that the latter is affected by the private information held by banks regarding their borrowers that is revealed to the capital market participants through the banks' strategy choices and conduct.

Similar to GZ, in order to accomplish this decomposition we use the empirical work of Berndt, et al. (2008), where the log credit spread on bond *j* issued by firm *i* at time *t* is a function of the probability of default ($EXDFT_t$) of the corporate firm and a vector of the bond/firm characteristics, $Z_{i,t}$, as represented in equation (2).

$$\ln(CS_{i,t}) = \beta EXDFT_{i,t} + \delta' Z_{i,t_t} + \varepsilon_{i,t} \quad (2)$$

where the zero mean disturbance $\varepsilon_{i,t}$ represents pricing errors. Calculating the average credit spread of all outstanding bonds for each firm in every period and given the probability of default of firm *i* at each period *t* (derived later in line with Merton (1974)) we were able to estimate equation (2) using an *OLS* regression.[9]

[8] In addition to the credit yield spread our study required data on the corporate firm's equity and debt, the return on equity, market value of the debt, and the corporate firm's use of banking loans. This information was obtained from the corporate financial statements and reports to the stock and bond markets. All firms that do not have the full information needed were deleted from the sample, further reducing the number of observations to 13,148.

[9] Equation (2) relates various variables to the credit spread. By construction, only variables that influence corporate bonds differently than they do government bonds, affect the credit spreads. Hence confounding macro factors and (matching) durations are unlikely to influence the credit spreads. Therefore we think that estimating equation (2) by OLS is in place. However to check for robustness we did also use other methods of estimation including the SUR methodology. The estimated coefficients of equation (2) are found insignificantly different between these various empirical methodologies and thus found robust.

The fitted value of the credit spread regression of equation (2), $\hat{C}S_{i,t}$ is averaged out across firms at period *t*:

$$\hat{C}S_t = \frac{1}{N}\sum_i \hat{C}S_{it} = \frac{1}{N}\sum_i \exp(\hat{\beta} EXDFT_{i,t} + \hat{\delta}' Z_{i,t} + \frac{\hat{\sigma}^2}{2}) \tag{3}$$

where $\hat{\sigma}^2$ is the estimated variance of disturbance term $\varepsilon_{i,t}$. The *EBP* in period *t* is simply[10] computed by

$$EBP_t = CS_t - \hat{C}S_t. \tag{4}$$

Given this decomposition we can estimate the forecasting power of the expected distance to default and the *EBP* in affecting economic activities.

In Appendix *B* we follow *GZ* and others in estimating the corporate firm's probability of default, using the distance to default framework developed in Merton (1974), and apply it to our data. Our sample runs from January 2003 until July 2011 and initially included 11,153 observations. After excluding extreme observations of *DD* values, our final sample has 8,752 observations.[11]

(Insert Figure 2)

Figure 2 displays the weighted average of *DD*, where the weights are the share of each firm's debt in total debt as of period *t* throughout our sample period.[12] We also marked the recession periods by the shaded vertical bars.[13] By construction, higher *DD* means lower default risk. We identify a decline in *DD* in the earlier months of 2003 (the second Intifada unrest), during the more recent recession of 2008, and recently in mid-2011. A very similar pattern is found in the average US firm *DD* (as

[10] We adopt the approach of Bleaney, et al. (2012) in constructing the *EBP*, where they subtract the fitted value of *CS* in (4) at the firm level and only thereafter average out. In contrast, *GZ* average out first and then subtract the fitted value. We deviate here from *GZ* because we don't have a complete data set for each bond characteristic and at every point in time.

[11] Following GZ, we eliminate from the sample all observations with a *DD* value of less than -2 or more than 20. We also check different cutoff values and find the results to be robust.

[12] In each month the average of *DD* values are weighted by the firm's debt as a share of total debt.

[13] Recession periods based on the Bank of Israel Composite State of the Economy Index (Marom, et al., 2003).

computed in GZ, although in periods of high growth the level of the Israeli *DD* is much lower than the value in the US.

In order to evaluate the risk premium embedded in the corporate bonds we regress credit spread *CS* on the $DD_{i,t}$ and other control variables that relate to bond specific characteristics including the term premium, the degree of liquidity (specified below), the bond's duration in years (*DUR*), the outstanding value of the firm's bonds (*PAR*) and the age since issued in days (*AGE*).[14] In order to compare our results with those of GZ, we include their results in the last column of Table B.3 in Appendix *B*.

Since the (lack of) liquidity in the capital markets may account for most of the price volatility in these markets, we also incorporate three alternative liquidity indices in the estimation of equation (2): (i) the one suggested in Amihud (2002) (denoted by *Liq_stock_d*); (ii) an index derived from Bid-Ask data (denoted by *Bid_ask_d*); and (iii) derived price elasticity in the bond market (denoted by *Elas_bond_d*). (For more details see Appendix *C*.) We then add the degree of the liquidity indices to the regression of the credit spread and report the results in Table *C*.1 (in Appendix *C*). All three estimate coefficients of the effect of liquidity are of the right sign and at a level of significance of at least at 10 percent. The estimate coefficients of *DD* remain intact, and so do most of the other variables.

5. *EBP* as Predictor to Economic Activity

We now decompose the credit spreads *CS* into its two components—the fitted value and the *EBP*—and then separately study the effects of each component on the economy (the growth of *GDP*; the growth of business product; unemployment and investment). To that end we re-estimate the regressions presented in Tables A.1 and

[14] The panel data regression also includes dummy variables for industries like construction and holding companies, fixed effects at the firm's bonds level and also a dummy variable for the 2008 recession. In some of the regressions we add other variables like dummy variables for the credit rating (*Dum_Rank*) that gets 1 for bonds rated A and above, and zero otherwise.

A.2 (Appendix A), where we replace the total credit spread with the two derived components as explanatory variables. The results are documented in Table 2.

(Insert Table 2)

The first column of Table 2 indicates that the excess bond premium is a predicator of GDP growth but insignificantly so for the business sector. The fitted credit spread explains GDP growth contemporaneously, while the EBP does so one quarter ahead. This last result is in line with Bleaney et al. (2012) estimators for the European corporate credit spreads, but the coefficient estimate of the *EBP* when the Israeli data are used, is much smaller than the European estimators and closer to the US estimator. Since unemployment lags *GDP* growth, it turns out that the two decomposed components of credit spread serve as leading variables, with 3–4 quarters lead over the quarterly changes in the unemployment rate. The decomposition of the credit spreads improves the goodness of fit of the regression in explaining the economic activity as reflected in the $adjR^2$ in all specifications.[15]

6. Commercial Banks and the *EBP*

So far we have shown that excess bond premium exists and that it does have some predictability power regarding the real business cycles. Our hypothesis is that information on banks' strategies which, in the case of a bond issuer is orthogonal to the *DD,* may affect the excess bond premium in the capital market. This information may be embedded in strategic choices banks make, which are not directly related to or derived from the single borrower's ability to repay his/her debt. For example, suppose that due to some aggregative (macro) realization, banks decide to require additional collateral from all borrowers belonging to a particular sector, which, given the asymmetry of information, should not in principle be applied *equally* or

[15] Regarding the lags that we report in Table 2, it is the best lag structure that we ended up getting in the regression, and indeed various combinations of lags were examined including the lag structure that is originally (before the decomposition) found significant and reported in Tables A:1 and A:2.

indiscriminately to all members of this sector. This requirement may induce capital market lenders to increase the bond premium they charge all borrowers who belong to that sector regardless of whether a particular borrower's distance to default was affected by the shock.

When such an aggregative development emerges and additional collateral is not feasible, banks could instead resort to loan loss provisions to cope with the expected realization of the aggregate development. This information on the banks' new provision, once realized in the capital market, may signal to the capital market lenders to require a higher risk premium. Yet because of the asymmetry of information between banks and their borrowers it sheds only partial light, or in some cases even no light at all, on the assessment of the borrower's *DD*. Credit crunch and credit rationing are other examples of a bank's strategies that convey valuable information to capital market participants regarding their pricing, yet do not fully affect the borrowers' *DD* because of the asymmetry of information.

As for the selection of explanatory variables in the *EBP* regression[16], since banks can mitigate the effects of the information asymmetry on the credit spreads by activating appropriate measures (strategies), the inclusion of the latters in that regression need be considered.

6.1 *The share of the firm's debt to commercial banks*

Another type of information that may affect the premium in the capital market with the same aforementioned characteristics is if a borrower in the capital market also has debt to commercial banks. Since banks have an advantage over the capital market lenders in monitoring and restructuring their borrowers' debt, the mere fact that a

[16] Earlier in the paper we note that the first component of the decomposition reflects the available firm-specific information *on the borrowing firm's financial health* and is by construction correlated with a measure of the probability of default of the corporate debt issuer. It is a very specific group of variables (according to Merton) that should enter the credit spread regression and we follow suit.

borrower is screened and followed by banks could be rather valuable for the capital market participants in pricing that borrower. It actually has two opposing effects on the bond premium. On the one hand, capital market borrowers could require a smaller premium since they can at least partly rely on the banks' handling of the borrower's repayment capability. On the other hand, since banks require collateral and capital market lenders usually require less, having debt to both may reduce the recovery share of the bond holders in a case of default, which implies requiring a higher bond premium in advance.

To verify the existence of these types of effects on the *EBP*, we empirically identify banks' strategies that are independent of the corporate firm's *DD* and then estimate the effects of these strategies on the *EBP*. We then utilize the following empirical methodology. At first we collect for each firm in our sample the share of its debt to the banking sector in its total debt (*SH*). In a panel regression of the *EBP* we used these shares as explanatory variables and found a significant negative coefficient, supporting our claim that capital market lenders that rely more on the banking sector (larger *SH*) have the advantage that banks handle their borrowers' repayment capabilities.[17] This negative relationship became more significant when we used fixed effect for the time periods. This result is consistent with the observation that most of the variability in these shares originates in the cross-sections. The negative sign in this regression remains intact when we replace the *SH* with a rank variable (*SHr*) that obtains a value of 1 (for *SH* smaller then 0.25) up to 4 (for *SH* higher then 0.75). We did not find a significant effect in the opposite direction, i.e. from the *EBP* to *SH* or *SHr*.

[17] In the regression we use the share of the debt to banks with two lags in order to overcome its endogeneity. The regression results can be obtained from the authors.

In the second stage we run similar regressions of the *EBP* utilizing time series data, the results of which are reported in Tables 3 and 3a. In these regressions we use quarterly averages of monthly *SH* and *SHr*, respectively, as well as of other banking variables that are reported by the banks. These variables may serve as *signals* to the capital market lenders and thus potentially affect their pricing of the bonds. In particular we use the banking global loan loss provision as a share of total outstanding loan balances (*gLLR*) and the bank's specific loan loss provision as a share of total outstanding loan balances, (*sLLR*)[18], as well as the growth of total bank credit (*credit_gr*), in the *EBP* regression. We also include the spread between the nominal interest rate on 6–12 month loans (*Int_gap*) and the Bank of Israel policy interest rate (*r_boi*) in this time series regression as indicators of the commercial banks' market power, as well as the *CDS* on Israeli government bonds (*CDS_Isr*), reflecting the exogenous country risk. All these variables appear in the regression with lags in order to deal with the potential endogeneity inherent in such regressions.

(Insert Tables 3 and 3a)

Note that the CDS on the government bonds is different from the other explanatory variables in that that it does not directly relate to banks. However we include it to control for the effect of the *exogenous* country risk on the *EBP*. Note that in applying the *VAR* (section 6.2) we include the stock market variables to control for the effect of the stock market on the *EBP*. This control is necessary since the shocks

[18] Specific loan loss provision is the bank's provision for realized loan losses. Global loan loss provision is the bank's provision for deterioration of loan repayments that cannot at that moment be identified with a specific borrower. When the bank resorts to g*LLR,* some of its borrowers' probability of default may be provided for twice. For example, consider a weak borrower who belongs to a certain sector *j* in the economy and who has already been provided for in the s*LLR* policy framework. Suppose now that in accordance with the prudential risk management the bank decides to provide for the whole sector *j* by increasing its *gLLR*. Our borrower is now provided for twice and the bank may decide as a result to reduce its excess *sLLR*.

we introduce affect the stock market as well. However, there is no need to control for the *CDS* in the impulse response since the various shocks do not affect the *CDS*.

In almost all regressions we found significant coefficients with the expected sign. The regression results are consistent with our hypothesis that a larger *SH* (as well as *SHr*) reduces the *EBP*, since the banks' monitoring of the firms' conduct as part of their prudential risk management strengthens capital market discipline. Similar regressions were estimated when the *EBP* as the dependent variable was replaced by the fitted credit spread, derived from the estimation of equation (2) (the results of which are reported in Table C.1 in appendix C). These regressions were found insignificant in explaining the fitted credit spreads. These results are indeed consistent with our hypothesis that banks' strategies affect the *EBP*.

6.2 *Applying VAR to identify the effects of banks' strategies on the EBP*

Although tables (3 and 3a) provide empirical support for our hypothesis, we in addition apply dynamics to our empirical tests in the form of *VAR* methodology to follow the impulse responses of the *EBP* to bank strategies' shocks. These shocks include a) an increase in the bank's *sLLR*, which reflects a shock to the banks' exposure to credit risk; b) an increase in the ratio of equity capital to risk-weighted assets, *CAP*, the banks either choose or required to hold; c) an increase in the banks' coverage ratio, defined as the ratio of total operational (non-interest) income to total operational expenses, *COV*. All of these shocks are conceptually unexpected increases in the banks' conducts. They all can be interpreted at least in part as shocks to bank strategies, and eventually they all affect the *EBP* in a way that is consistent with the bank strategies, revealing relevant information in the capital market. These findings complement the results shown in Tables 3 and 3a, and support our hypothesis that banking strategies affect the pricing in the capital market through its effect on the *EBP* and in a predictable way.

Specific loan loss reserves are usually strategic variables and in particular regarding the timing of the provisions. The instrument variables we use in the case of the shock to the *sLLR* can be identified as bank strategic conducts (see section (a) below for the discussion of the *IV* for the *sLLR*). Basle indiscriminately instructions regarding the required capital ratio make the individual bank's capital ratio a strategic decision. The *required* capital ratio is almost the same for all banks, so for a bank to hold higher capital ratio it must be for strategic reason. For the case where the shock is to the coverage ratio, it could go either way, it could be bank strategic as well as non-strategic. However, the on-impact impulse response of the *EBP* in this case is dynamically similar to those of the other shocks.

The *VAR* estimations include in addition to the *sLLR*, *gLLR*, *CAP* and *COV* the following variables: The option-implied volatility on the *TA100* (*VIX*) traded on the Tel-Aviv stock exchange and the (value-weighted) market excess return (*MER*) to control for the effect of the stock market on the *EBP*; and the firm's debt to commercial banks as a share of its total debt (*SHr*), which has already been found to have significant influence on pricing in the capital market. Other variables are the leverage of the bank (*LEV*); the bank's problem loans as a share of total outstanding loan balances (*PRL*); and the profitability of commercial banks, (*ROA*).[19]

It can be argued that some of the banking data are reported in book time rather than real time data and since bank quarterly report comes with a substantial lag, we actually use "future" data. In Israel the banking reports are usually received with a lag of two and half months (less than 1 quarter). Therefore, for the independent variables

[19] The ratio of net profit to total assets of the banking sector.

in the regressions (reported in Tables 3 and 3a) with one quarter lag, they may suffer from this problem. But for all independent variables with two quarter lag (*SH* and *SHr* in particular) there is no problem of that kind, because the banking data are in before the end of the two lagged quarters. More importantly, in the impulse responses of the *VAR* methodology all explanatory variables appear with two quarter lag and thus do not suffer from this problem.

To rationalize our view that shocks to banks' strategies affect the pricing in the capital market, we need to assume that there exist as aforementioned two types of information asymmetry: between borrowers and lenders (including the banks) and between the capital market lenders and the banks. Absence of the information asymmetry will have the bank's shock affecting the *DD* of the borrowing firm rather than its *EBP*, assuming that the bond market is efficient.

Since we are interested in the on-impact impulse responses of the *EBP* independently of the on-impact effects of the stock market responses, we neutralize the effects of the latter by designing the order of the variables in the *VAR* such that the on-impact effect of the stock market will be orthogonal to the shock in all of the shocks. The results of the *VAR* are displayed in the following Figures 3–5. We estimate the *VAR* representation for the period 2003:Q1 to 2011:Q3 using a lag of two periods for each endogenous variable, and also include a dummy variable for the 2008 global financial crisis.

The shock to the *sLLR* generates an announcement effect which causes capital market lenders to change their required risk premium by shifting the *EBP*. However, because of the information asymmetry between borrowers and lenders, the latters (with the inferior information) charge higher risk premium from all borrowers, indiscriminately, regardless whether the borrower is good or bad. The other shocks we introduce generate, in addition to the announcement effect, an expected relocation of borrowers that motivates capital market participants to further readjust their pricing through the *EBP*. Here the asymmetry of information between lenders (banks and capital market lenders) matters as well. Banks are known to have better information due to the monitoring they undertake, and are thus capable of revealing relevant information to the market participants.

a) An increase in the sLLR – a realization of higher exposure to risk

The impulse response functions to a shock to the *sLLR* are displayed in Figure 3. The stock market is represented here by the *MER*, and it is designed to be on-impact orthogonal to the shock. In the top panel of Figure 3 the shock is displayed as well as the impulse responses of the *MER*. Here we design the *VAR* dynamics such that the *gLLR* will also be on impact orthogonal to the original shock, so that it will not counter on impact the effects of the examined shock.

(Insert Figure 3)

As for the main results, we get that on impact, the banking leverages increase insignificantly while the *SHr* remains constant, indicating a weak reaction if any by commercial banks to the shock. However, the *EBP* increases significantly on impact, which is consistent with the possibility that the mere knowledge of the bad realization in the banking *sLLR* (an announcement effect) is relevant in pricing the firm's bond premium, i.e. requiring a larger premium in the bond market.

Three types of criticism can be made regarding this last impulse responses. First, the *sLLR* should be highly correlated with the risk of the borrower and thus it should affect the bond premium directly through the *DD*. In order to examine the validity of this argument we replace the *sLLR* with the *gLLR* which may be correlated with a group of sectorial borrowers of which some are good and sound and others are less so. By definition it does not correlate with the *DD* of a particular borrower. The on-impact results of the impulse response to a shock to the *gLLR* (see figure D.1 Appendix *D*) are similar to the shock to the *sLLR*.

Second, it may be argued that the *sLLR* is endogenous and thus suffers from the endogeneity problem. To overcome this problem we use the ratio of *sLLR*/*PRL* as an *IV* for the *sLLR*, where this ratio reflects the strategic decision of banks regarding the appropriate timing to provide for a loan loss given that the borrower is already identified as problematic. This is a strategic policy and can serve as *IV* in this case. Again the impulse response functions (see figure D.2 Appendix D) are similar to those we find in the original impulse responses to the shock to *sLLR*.

Finally, it can be argued that these results are specific to the Israeli banks. To test this argument we use *GZ*'s *US* data to reproduce *GZ* impulse response functions to a shock to the broker-dealer's excess return (Figure 9 in *GZ*'s paper). We then replace this shock with a shock to the US banks' data on *LLR*. However, because of the possible endogeneity of *LLR*, we use the US banks' data on the banks' write-offs to construct forward guidance in the form of recovery rates.[20] This forward guidance can then be used as an instrumental variable to identify the influence of US banks' strategies on pricing in the capital market. We note that the recovery rate in the near future is unknown and its realizations can be used as shocks. See Gertler and Karadi (2014), who use similar methodology for the identification in implementing the *VAR*. In practice, we run an OLS regression of the US *LLR* on the write-offs, and use the residual (*LLR_REC*) as an *IV* in the following *VAR.*[21] The results are displayed in Figure D.3 (in Appendix D), where the on-impact impulse response of the *EBP* is again similar to what we found using the Israeli bank data (Figure 3).

[20] The share of problematic loans that is recovered by the commercial banks.
[21] The details of this regression result can be obtained upon request from the authors.

b) An increase in the capital ratio – expectations for higher realization of risk

In the top panel of Figure 4, the shock to the capital requirement is displayed as well as the on-impact orthogonality of the stock market responses (as is displayed by the *VIX*) to the shock. In other words, on impact, the VIX does not respond to the shock.

(Insert Figure 4)

The next three diagrams in Figure 4 show the on impact impulse response functions of commercial banks to the shock. In particular, both the leverage and the share of the firm's debt decrease on impact, while *sLLR* remains unchanged. These responses are consistent with the assertion that, in response to the shock, commercial banks refuse to grant loans to some (possibly weaker) borrowers, who then reluctantly turn to the capital markets. Indeed as shown in the bottom panel of Figure 4, the capital market reacts by requiring a higher bond premium on-impact, which is reflected in the on impact increase of the *EBP*. Due to the asymmetry of information regarding the borrower's repayment position, there could very well emerge a situation following the aforementioned shock where some good borrowers' demands for bank loans will be turned down. This is why their *DD* does not accurately reflect these new borrowers' risk. The resulting responses (shown in Figure 4) are consistent with our hypothesis that banks' strategies may affect pricing in the capital market through their effects on the *EBP*.

c) *An increase in the bank COV – a realization of larger market power and/or lower net cost of provision of financial services*

This shock reflects either a decrease in the bank's marginal operating costs or an increase in the bank's operating income, or both. As before, on impact the *MER* is orthogonal to the shock and the related impulse responses are as follows. Here we take advantage of the fact that commercial banks determine this ratio in accordance with their market power and operating costs. When market power increases, commercial banks will receive more noninterest income relative to interest income, and the *COV* will therefore increase. In addition, a positive shock to the *COV* could also represent a realization of lower operating costs in the provision of financial services, making it less necessary to seek a higher return, which implies higher *COV* and lower exposure to risk.

The impulse response functions to this shock are shown in Figure 5. On impact, the banks' leverage and *sLLR* fall and the *SHr* is also reduced, although insignificantly. As far as the banks' optimal choices are concerned, all of these responses are consistent with one another following the realization of lower net cost of provision of financial services.

(Insert Figure 5)

As for pricing in the capital market, the lower exposure to risk by the commercial banks can justifiably be interpreted as a shift of weak borrowers from banks to the capital markets and, in light of the asymmetry of information, some of these borrowers are actually financially sound. Consequently, these changes could not be fully reflected in the *DD,* leading capital market lenders to require a higher premium, as is indeed reflected in the higher *EBP* (see Figure 5).

It could be argued that a realized increase in the coverage ratio will be followed by a decrease in the banking interest rate gap between the loan rate and the deposit rate (profit management known as cross-subsidy). Our impulse response of the interest rate gap to the shock shows no sign of such a development.

To check the robustness of the impulse response results that are shown in Figure 5, we examine the impulse response to a shock to the interest income margin which can also be interpreted as a shock to the utilization of market power. Indeed the findings (see Figure D.4 in Appendix D) are similar to the impulse responses shown in Figure 5.

7. Conclusions

This paper builds on the framework introduced by GZ, where they find that the credit spreads contain informative content with regard to the real business cycles. They decompose the credit spread into the bond risk premium based on the probability of default of the bond issuer and the derived residual which they refer to as an excess bond premium. They find that this derived excess bond premium is a good predictor of real business cycles and thus a good leading indicator. We reproduce GZ’s results using Israeli capital market data and aim to explain the causes for the dynamics of this derived excess bond premium that makes it a good leading indicator of the real business cycles.

To that end we propose and show that this excess bond premium reflects, among other things, the commercial banks' influence on the corporate firm’s pricing of its bonds traded in the capital markets. To support this proposition we find empirical evidence of the relationship between the excess bond premium and the corporate firm’s debt to the banking sector as a share of its total debt. We find that the larger the share, the smaller the excess bond premium, implying that the commercial banks’ capability of monitoring and following their clients and their prudential risk management can be counted on in determining and pricing the bond premium. Consequently the bond holders can therefore be satisfied with a smaller premium.

We use *VAR* estimation and generate impulse response functions to shocks to the banks’ strategic (including policy) choices, and find that a positive shock to the bank’s capital ratio on impact causes a rise in the excess bond premium. So does a positive shock to the specific loan loss reserves, and similarly a positive shock to the bank’s coverage ratio that positively affects the required bond premium. In conclusion, we notice that the excess bond premium is not only a leading indicator for the real business cycles, but also a channel through which the banking sector affects these cycles.

Appendix A. Credit Spreads and Economic Activity

In this appendix we study the relationship between credit spreads and current economic activity and whether the credit spread is a leading indicator of fluctuations in the real business cycles. To that end, and in the spirit of GZ, we estimate the following equation:

$$dY_t = \alpha + \beta dY_{t-1} + \gamma CS_{t-1} + \lambda RB_{t-2} + \phi Z_t + \varepsilon_t \qquad \text{(A:1)}$$

where Y_t denotes the level of real activity and $dY_t = \ln(Y_t / Y_{t-1})$; *CS* denotes our credit spreads which, for our hypothesis, should appear in the estimation with one or more lags. Alternatively we replaced our *CS* by the yield difference between BBB-rated and AA-rated corporate bonds; *RB* is the real short-run interest rate, captured by the Bank of Israel's nominal interest rate net of the expected inflation[22] (with a lag of 2 quarters); Z_t is a vector of exogenous control variables such as changes in world trade and a dummy variable for the third quarter of 2006 reflecting the effect of the second Lebanon war, which took place at that time, on the Israeli economy; and finally ε_t is the forecast error.

In the regression of equation (A:1) we include as control variables: the slope of the treasury yield curve[23] reflecting the term structure; the real short-term key policy rate, reflecting monetary policy; and the growth of world trade (*WTO_GR*), reflecting the global demand for the Israeli exports, recalling that the Israeli economy

[22] Expected inflation is derived from the yields on the CPI-indexed and nonindexed bonds that are traded in the Israeli capital market.
[23] The ratio of the 10-year Treasury yield to the one-year yield.

is a small open economy. Our equation helps in examining the marginal informative content of the credit spreads, conditional on the aforementioned indicators. In the estimation we utilize four quarterly economic activity indicators: (i) the growth of the real *GDP* (*GDP_GR*); (ii) the growth of domestic business product (*GDPBS_GR*); (iii) the change in fixed capital formation (*INV_FX*); and (iv) the change in unemployment rate (*DU*). The estimated results of equation (A:1) for each of the dependent variables are reported in Tables A.1 and A.2.

Table A.1. GDP and GDPBS Regressions

(Quarterly data in annual terms)

Financial Indicator		GDP_GR			GDPBS_GR	
RB(-2)	-0.531**	-0.688	-0.396	-0.497*	-0.496	-0.626**
	[2.44]	[1.34]	[1.60]	[1.95]	[1.59]	[2.70]
WTO_GR	0.799***	0.636***	0.680***	1.023***	1.128***	1.109***
	[6.61]	[5.09]	[5.15]	[7.05]	[7.19]	[6.89]
BBB_AA(-1)		-0.211***			-0.107	
		[3.15]			[1.34]	
CS(-1)			-0.280**			-0.135
			[2.52]			[1.08]
Constant	5.400***	3.860**	7.400***	5.804***	7.595***	8.146***
	[5.34]	[2.61]	[6.56]	[5.17]	[6.27]	[7.53]
Adj.R^2	0.682	0.833	0.750	0.721	0.853	0.817

NOTE: Sample period 2003:Q2–2011:Q3. Each specification also includes a constant, GDP growth in the previous quarter, term spread variable and dummy for the Second Lebanon war (not reported). The values of the *t*-statistics are reported in brackets. *** Significant at the 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table A.2. Unemployment and Investment Regressions

(first difference)

Financial Indicator		DU			INV_GR[1]	
RB(-2)	0.095**	0.028	0.054**	-0.628**	-0.292	-0.434
	[2.25]	[0.84]	[2.35]	[2.26]	[0.66]	[1.06]
WTO_GR	-0.095***	-0.131***	-0.117***	0.424*	0.482*	0.490**
	[4.52]	[6.76]	[6.21]	[1.71]	[2.00]	[2.09]
BBB_AA(-2)		0.024			-0.349**	
		[1.62]			[2.20]	
***CS*(-2)**			0.042**			-0.700**
			[2.55]			[2.55]
Constant	-0.374**	-0.242	-0.366**	2.657***	3.306**	5.224***
	[2.17]	[1.59]	[2.53]	[2.87]	[2.25]	[3.37]
Adj. R^2	0.544	0.678	0.648	0.136	0.126	0.270

NOTE: Sample period 2003:Q2–2011:Q3. Each specification also includes a constant, dependent variable with one lag, and term spread variable (not reported). The values of the *t*-statistics are reported in brackets. *** Significant at the 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.
1. In quarterly terms.

There are two panels in each of these Tables, where each panel corresponds to a different dependent variable. The first column in each panel is considered the baseline regression results. It is empirically evident that in each of the baseline regressions there are significant negative (positive in the DU regression) effects of the real short-term interest rate with a lag of two quarters and significant positive (negative in the DU regression) effects of the increase in the growth of world trade.

The remaining two columns in each panel describe the results of the baseline regressions augmented by the two credit spread indicators. The latter were found to have significant negative effects on the GDP growth and on the growth in investment with a lag of one and two quarters, respectively. On the change in unemployment only the credit spread *CS* (as opposed to the BBB_AA spread) was found to have a significant positive effect with a lag of two quarters. In fact, the inclusion of the credit spreads in the regressions (relative to the baseline) improves the goodness of fit as measured by the adjusted R^2 in most of the panels. The magnitude of the estimated coefficient of the *CS* spread is insignificantly greater than those of the BBB_AA spreads.[24] A current increase of 100 basis points in the *CS* credit spread implies an almost 0.28 percentage point (annual) drop in GDP growth in the next quarter. The standardized estimate of the *CS* spread is about 0.4 and is similar to the estimator for the US spread in *GZ* (2012).

The bottom line of all this analysis is that using Israeli data, the credit spreads were found to be leading indicators of the real business cycles. That is, there is informative content in the credit spreads that help in forecasting real activity. We

[24] We use the Wald test to examine whether the two estimates are significantly different. The sample period in the regression that includes the difference between the BBB-rated and the AA rated corporate bonds is shorter (2005:Q3–2011:Q3) with respect to the other regression. Utilizing the same sample period for regressions that have different indicators of credit spreads results in an insignificant difference in the adjusted R^2.

study this informative content and in particular its relationship with the financial intermediaries (commercial banks).

Next in this appendix we display (see Table A.3) and examine the results of the credit spread (*CS*) regressions in which the explanatory variables include the default risk measurement *DD*. These regressions are necessary for the decomposition of the credit spreads and the construction of the *EBP*.

The difference between the three regressions, (columns (1)–(3)) is that regressions (2) and (3) include a Liquidity index and the third regression (column (3)) also includes the dummy variable *d_Rank* (equals 1 if the bond rated *A* and above, and 0 otherwise). From the results documented in Table A.3 we find that the elasticity of the credit spread with respect to the *DD* in each of the four regressions including that of *GZ* are statistically similar and significant. In addition we see that a larger duration of the debt reduces these elasticities as shown in the significant positive coefficient of the interaction variable *DD**ln(*DUR*).

Table A.3. Credit Spreads (logs) and the Distance to Default

(Panel- Data-fixed effect)

Explanatory variable	*(1)*	*(2)*	*(3)*	*(4) U.S data GZ (2012)*
-DD	0.095*** [11.8]	0.076*** [10.6]	0.066*** [7.37]	0.075*** [15.0]
ln(*PAR*)	-0.135*** [9.46]	0.088*** [5.35]	0.151*** [9.56]	0.171*** [9.5]
ln(*AGE*)	-0.047*** [4.64]	-0.042*** [4.25]	-0.017* [1.66]	0.047*** [5.87]
ln(*DUR*)	-0.477*** [6.57]	-0.597*** [8.77]	-0.426*** [6.09]	0.106*** [5.88]
***-DD**ln(*DUR*)**	-0.024*** [4.73]	-0.021*** [4.39]	-0.017*** [3.60]	
Liq index		0.382*** [27.5]	0.308*** [18.6]	
d_Rank	NO	NO	YES	YES
Adj.R^2	0.481	0.571	0.379	0.649
No. Obs.	8,752	8,750	8,750	346,126

t-statistics are reported in brackets. *** Significant at the 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

As for the effect of the Duration on the credit spread there are two possibly opposite effects. Higher Duration implies higher exposure to risk because of the uncertainty regarding the future, thus a positive effect of duration on credit spreads is likely to emerge, similar to the result in *GZ* (2012). But longer duration increases the probability of exiting from bad times and thus moderates the aforementioned positive effect of duration on the CS. This latter effect is captured by the estimate coefficient of the interaction *DD**ln(*DUR*). Brodesky (2011), who utilizes similar Israeli data, got a negative effect of Duration on the credit spreads.

Appendix B. ***Measuring the Probability of Default*** [25]

For the decomposition of the credit spreads, and in line with GZ, we estimate the firm's probability of defaults using the *distance to default* (*DD*) framework developed in Merton (1974). The derivation of the probability of default is based on the claim that the equity of firm, *E*, can be viewed as a call option on the underlying value of the firm, *V*, with a strike price equal to the value of the firm's debt, *D*.

The first assumption in this framework is that the value of the firm follows a geometric Brownian motion (see equation 4 in GZ), that is:

$$dV = \mu_V V dt + \sigma_V V dw , \qquad \text{(B:1)}$$

where V is the unobservable value of the firm, μ_V represents the expected return on V; σ_V is the volatility of the firm's value, and dw is an increment of the standard *Weiner* process. We further assume that the firm has just issued a single discount bond in the amount D in T periods.

According to Black-Scholes - Merton option-pricing framework, the value of the firm's equity is :

[25] In this appendix we closely follow *GZ* in the derivation of the firms' *DD*.

$$E = V\Phi[K_1] - e^{-rT} D\Phi[K_2] \tag{B:2}$$

Where r is the risk free interest rate; Φ is the cumulative standard normal distribution function $K_1 = \frac{\ln(V/D) + (r + 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}$; and $K_2 = K_1 - \sigma_V \sqrt{T}$.

Taking the forecasting horizon to be one year, i.e. T=1, we can use the monthly 1-year treasury yield for r. We estimate σ_E from historical daily stock returns using a 180-day moving window.[26] The debt is equal to the sum of the firm's current liabilities and one-half of its long-term liabilities.[27] Similar to GZ, we use the procedure of Bharath and Shumway (2008) to derive the initial value of σ_V from the following $\sigma_v = \sigma_E (D/(E+D))$.

Utilizing equation (B:2) and the derived σ_V enables us to compute the firm's monthly value V. With this new time series of V we calculate the implied monthly return *dlnV* and new estimates for μ_V and σ_V. We then repeat this iteration again and again until convergence is accomplished.

The resulting solutions of this framework allow us to calculate the firm's "distance to default" in each month over a one-year horizon as follows:

$$DD = \frac{\ln(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V} \tag{B:3}$$

A default occurs when $\ln(V/D) \le -(\mu_V - 0.5\sigma_V^2)$. The implied probability of default is given by $\Phi(-DD)$.

[26] We take the observation of the last day in each month as the relevant monthly data.

[27] Moody's and others use the same assumption in constructing their expected default frequencies (EDF). This assumption comes from the fact that short-term debt requires a repayment relatively soon whereas long-term debt requires the firm to pay only the coupon payment.

Appendix C. ***Liquidity in the credit spread equations***

Since the available liquidity in the capital markets may account for most of the price volatility in these markets, we incorporate three liquidity indices in our study: (i) taken from Amihud (2002) (denoted by *Liq_stock_d*); (ii) derived from the Bid-Ask data (denoted by *Bid_ask_d*); and (iii) based on the direct computation of price elasticity in the bond market (denoted by *Elas_bond_d*). The *Liq_stock_d* index represents the degree of liquidity in the stock market, and is derived from firm *j* stocks at month *t* by

$$Liq\_stock\_d_t = \frac{1}{N_{jt}} \sum_{i=1}^{N_{j,t}} \sqrt{\frac{|R_{jit}|}{VOL_{jit} P_{ji-1t}}}$$

where N_{jt} is the number of trading days in the stocks of firm *j* during month *t*; R_{jit} is the daily return on the stock of firm *j* on day *i* within month *t*; VOL_{jit} is the trading volume of shares of firm *j* on day *i* of month *t*; and P_{ji-1t} is the closing stock price of firm *j* on day *i*-1 of month *t*. This index is smaller when liquidity increases.[28]

Table C.1. Credit Spreads (in log), Distance to Default and Liquidity Indices

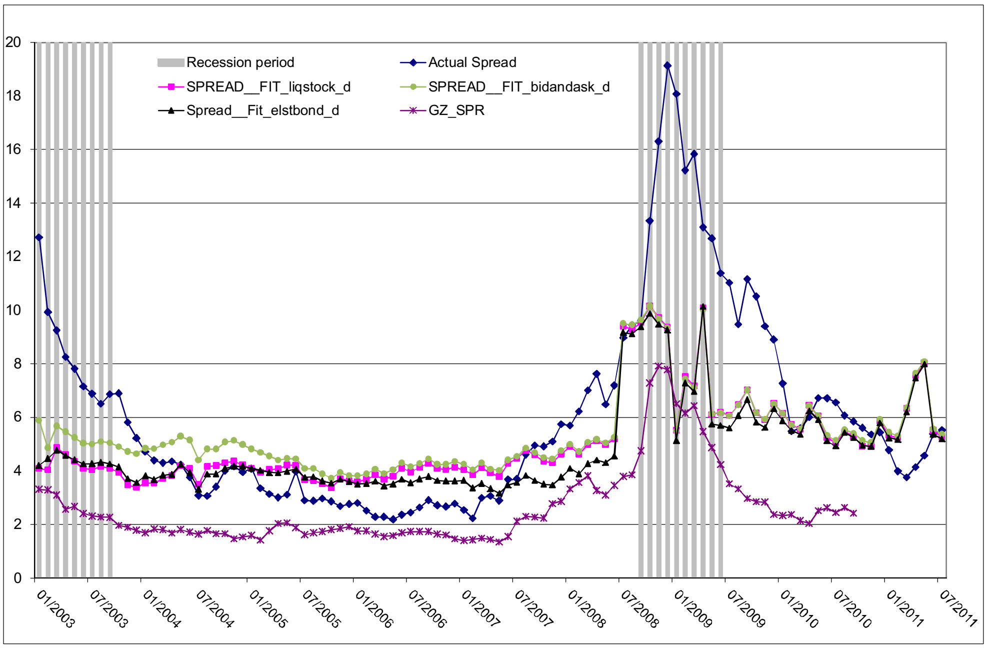
Explanatory variable	*(1)*	*(2)*	*(3)*
-DD	0.076*** [10.6]	0.074*** [9.81]	0.090*** [11.9]
Liq_stock_d	0.382*** [27.4]		
Bid_ask_d		0.363*** [33.9]	
Elas_bond_d			0.105*** [25.3]
Adj. R^2	0.571	0.572	0.492
No. Obs.	8,750	8,750	8,750

Notes: The three regressions contain all the explanatory variables that appear in the regressions of Table A.3 but are not reported here. The *t*-statistics are reported in brackets. *** Significant at the 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

[28] For elaboration see Amihud (2002).

We note that the relevancy of this index in measuring the liquidity position depends on the validity of the assumption that the degree of liquidity of firm *j* in the stock market is a good indicator of its liquidity position in the bond market. The Index *Bid_ask_d* represents the degree of liquidity as it transpires from the daily average spread between the bid and the ask values in the bond market for each firm *j*. The larger is this spread the less liquid the market is for the specific bond.[29]

Figure *C*.1. Israeli Average Credit Spreads, Predicated Israeli Credit Spreads and the US GZ Credit Spreads



Finally the *Elas_bond_d* liquidity index is derived from the inverse of (direct computation of) elasticity of firm *j*'s outstanding bond balances with respect to its daily return.[30] The larger this inverse elasticity index is (in absolute value) the less liquid the firm's bonds are. To normalize the liquidity indices we transformed each index to the "degree" of liquidity, which includes four possible levels, from the highest liquidity position (marked by the value 1) to the lowest liquidity position

[29] For more details see Gamrasni (2011).

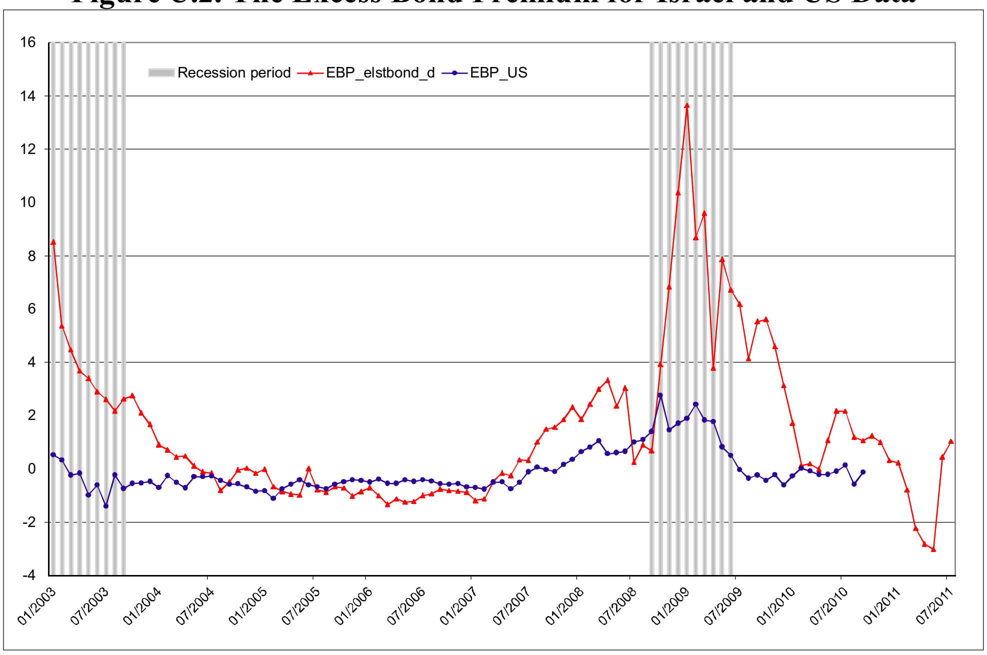
[30] The inverse of the elasticity is calculated as follows $\eta^{-1} = \dfrac{\partial r}{\partial b} \Big/ \dfrac{r}{b}$ where *r* is the average daily return on the bond and *b* is the average outstanding balances.

(marked by the value 4). We further assumed a uniform (flat) distribution such that each group of firms with degree of liquidity *k*, *k*=1,…,4, contains 25 percent of the sampled population.

We now add the degree of liquidity indices to the regression of the credit spread and report the results in Table *C.1*. All the three estimate coefficients are of the right sign and of at least at 10 percent significant level. The estimate coefficients of *DD* remain intact, as did most of the other variables. Note that even if there is some endogeneity in these liquidity indices, it doesn't affect significantly the results.

Figure *C*.1 displays the monthly average of daily credit spread data (percentage point) alongside the fitted values of the regressions that include the three liquidity indices, where each one appears separately in the sample period 2003:M1–2011:M7. The Figure also includes the average credit spread of US data (GZ_SPR) that was taken from GZ (2012). Over most of the sample period the spread and the three fitted spreads are relatively small. They increase sharply in the wake of the financial crisis (mid–2008 until mid–2009). In this case there emerges a substantial gap between the actual credit spreads and the predicted (fitted) credit Spread.

Figure *C*.2. The Excess Bond Premium for Israel and US Data



All three fitted credit spreads are correlated with each other. As such, we focus on the predicted credit spread that uses the inverse elasticity as the liquidity index (*Spread_fit_elasbond_d*). Consistent with equation (4), and in line with GZ, we define the *EBP* by the difference between the actual credit spreads and the fitted values.

Figure *C*.2 displays two series of the monthly average of daily *EBP*, one for the Israeli data (denoted *EBP_elasbond_d*) and another for the US that is taken from *GZ* (2012) (denoted *EBP_US*). Similar to *EBP_US*, the *EBP_elstbond_d* increased significantly prior to or during cyclical downturns. In the 2008 recession, it starts to increase somewhat earlier—at the end of 2007 and the first half of 2008.[31]

Appendix D. ***Auxiliary Impulse Response functions***

In this appendix we present four auxiliary impulse responses to shocks that complement the analysis in section 7. In addition a summary statistics of variables that appear in the *VAR* estimation are displayed in Table D.1.

Table *D*.1. Summary Statistics of variables in the VAR estimation

Variable	Mean	SD	Min	P50	Max
MER (pct.)	14.9	31.7	-55.3	14.2	84.3
VIX	22.5	6.8	15.3	19.6	47.7
sLLR	0.24	0.08	-0.03	0.25	0.42
PRL	0.072	0.016	0.045	0.071	0.096
gLLR	0.008	0.013	-0.028	0.008	0.037
LEV	16.5	1	14.8	16.4	19.1
CAP	11.56	1.33	10.14	10.98	14.23
COV	0.58	0.05	0.46	0.59	0.70
ROA	0.002	0.000	-0.001	0.002	0.003
Credit_gr	0.009	0.016	-0.036	0.008	0.043
SH	0.394	0.098	0.308	0.342	0.622
Int_gap	0.033	0.009	0.015	0.032	0.056

Sample period: 2003:Q1–2011:Q3.

Auxiliary impulse response functions

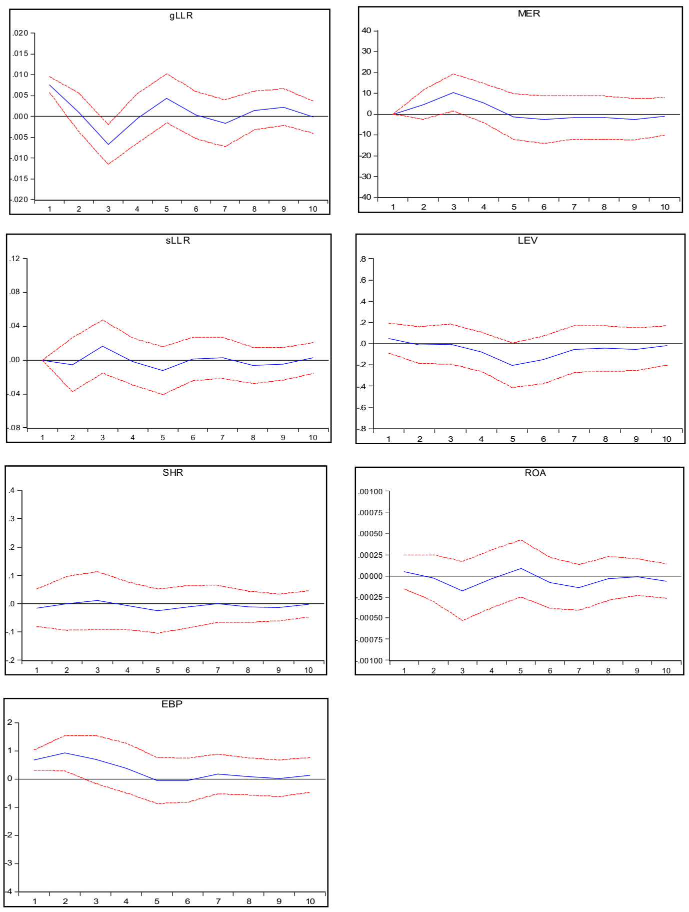
[31]By construction, the *EBP* in the panel data and also the US data are uncorrelated with the fitted credit spreads. But in the time series dimension the average fitted credit spread and the average *EBP* have some correlation (as shown in the Figures 3 and 4) but this relationship is spurious.

D.1 *An increase in the commercial bank's exposure to risk as reflected by the gLLR*

The dynamics created by this shock are shown in Figure D.1. In this impulse response function, we design the VAR dynamics such that the specific loan loss provision *sLLR* will be orthogonal on impact to the shock, so that it will not counter the shock. The stock market is represented by the *MER*, and as in all impulse response functions, it is also designed to be on-impact orthogonal to the shock.

According to the estimation, the impulse responses to the positive shock to the *gLLR* are similar on impact to the responses that transpired following the shock to the *sLLR* (shown in Figure 3 in the text). It seems to suggest that similar to the effect of a shock to the *sLLR*, the unexpected increase of the *gLLR* is informative for the capital market participants, mainly through its effect on pricing in the bond market, where the only significant on-impact response transpires.

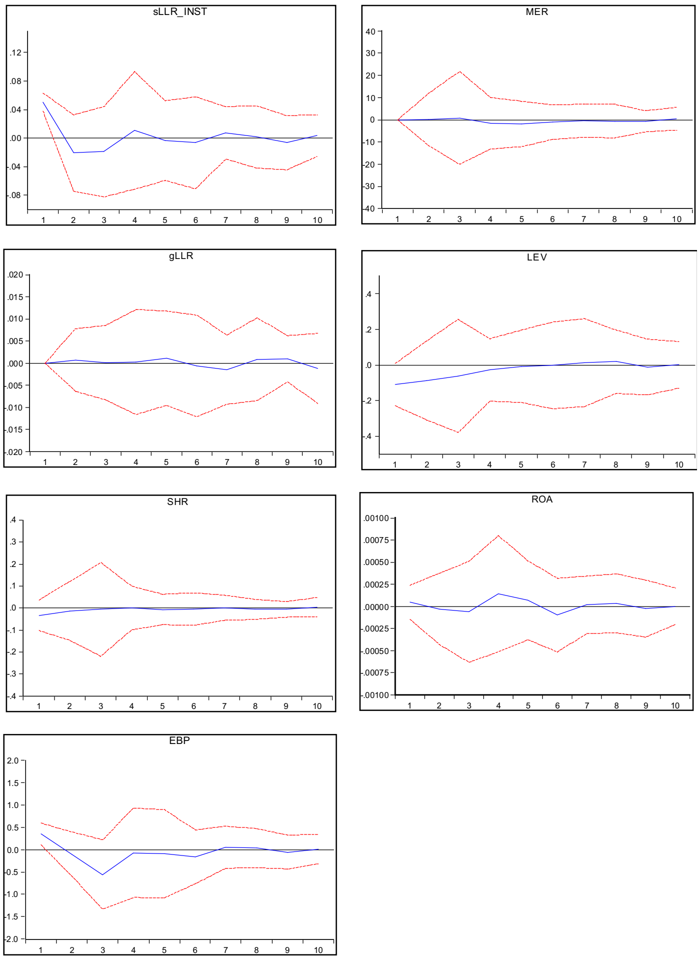
Figure *D*.1. Implications of a shock to *gLLR* on banks' conducts and on the *EBP*



D.2 *An increase in the commercial bank's ratio of the sLLR to the PRL*

In this case we use the ratio of the *sLLR* to the *PRL* as an instrument variable for the *sLLR*, and utilize the standard 2SLS procedure. The impulse responses are shown in Figure *D*.2, where it can be seen that the on-impact responses are qualitatively the same as in Figure 3.

Figure *D*.2. Implications of a shock to *sLLR_INST* on the *EBP*

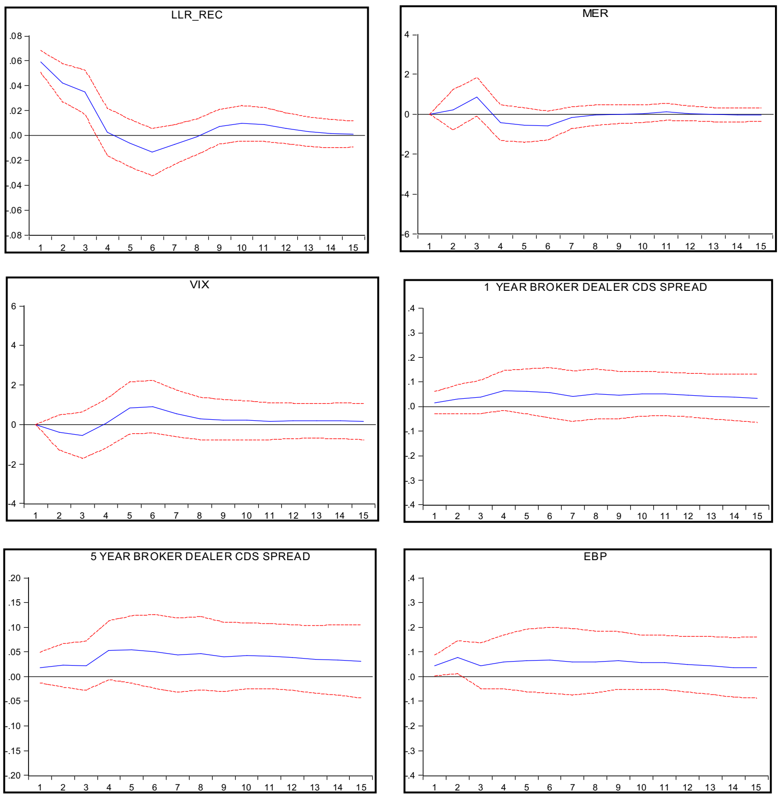


***D*.3** *An increase in the commercial bank LLR (US data)*

Here we reproduce the GZ impulse responses to shock to the broker-dealer excess return and then replace this shock with the US banks' data on *LLR*. However, because of the possible endogeneity of *LLR,* and since we have data on the US banks' write-offs of loans, we can construct a forward guidance in the form of the recovery rate. This forward guidance can then be used as an instrument variable to identify the influence of US banks' strategies on pricing in the capital market. We note that the recovery rate in the near future is unknown and its realizations can be used as shocks. See Gertler and Karadi (2014), who use this methodology in implementing *VAR*.

We run an OLS regression of the *LLR* on the charge-offs and use the residual (LLR_REC) as an instrument in the following *VAR*. The results are shown in Figure D.3 where the on-impact impulse response of the *EBP* is similar to what we found using Israeli bank data (Figure 3).

Figure D.3. Implications of a shock to *US data LLR* on the *EBP*

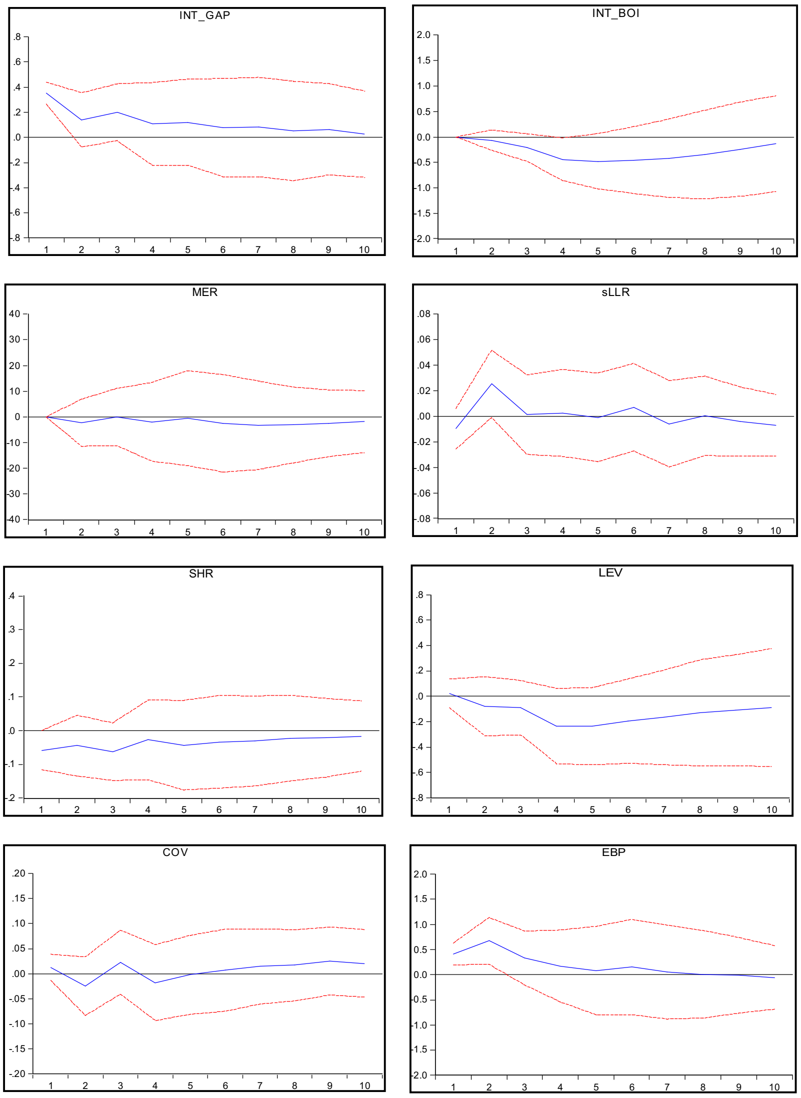


D.4 *An increase of the interest income margin, Int_Gap*

With this shock we study the reactions of commercial banks and the *EBP* to an increase in the *Int_Gap* between the bank lending rate and the monetary policy rate (which is a good proxy for the interest income margin). This shock may reflect higher market power of commercial banks. The impulse response functions are shown in Figure *D*.4.

A comparison of the on-impact responses here to the responses to a shock to the *COV* shown in Figure 5 supports the hypothesis that the two shocks qualitatively generate the same responses and probably originated in the same type of shock. We argue that the original shock could very well be a shock to the market power of the banks in Israel.

D.4. Implications of a shock to *Int_Gap* on banks' conducts and on the *EBP*



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Tables:

Table 1. Summary Statistics of Corporate Bond Characteristics

Variable	Mean	SD	Min	P50	Max
Number of CPI-indexed corporate bonds per firm/month	1.89	1.56	1.0	1.0	14
Number of nonindexed corporate bonds per firm/month	1.65	1.10	1.0	1.0	8
Market value of issue (NIL million, constant prices)	512	1,348	0.0336	96.5	19,950
Maturity at issue (years)	8.2	2.6	1.55	7.5	21.7
Term to maturity (years)	5.3	2.6	0.0219	5.1	21.6
Duration (years)	3.0	1.5	0.40	2.8	15.1
Credit rating (Moodey's)			D	AA-	AAA
Credit spread on CPI indexed corporate bonds (pct.)	7.13	8.76	0.016	3.80	49.78
Credit spread on unindexed corporate bonds (pct)	3.68	6.42	0.0016	1.81	49.79

Note: Sample period: 2003.1–2011.7, Number of firms = 688.
Sample statistics of the top 7 rows are based on the original collected data, Observations = 23,606.
Sample statistics on the credit spreads are based on trimmed data (see text for details), Observations = 18,502.

Table 2. The Excess Bond Premium and Economic Activity

Financial Indicator	GDP_GR	GDPBS_GR	DU	DU
	(1)	(2)	(3)	(4)
***RB*(-2)**	-0.540	-0.593	0.043	
	[2.62]	[3.70]	[1.40]	
WTO_GR	0.593	0.865	-0.110	0.118
	[5.35]	[7.27]	[6.59]	[7.20]
CS_PR	-0.710	-0.796		
	[3.54]	[5.86]		
***EBP*(-1)**	-0.241	-0.128		
	[2.31]	[1.43]		
***CS_PR*(-2)**			0.029	0.007
			[1.27]	[0.40]
***EBP*(-4)**			0.033	0.035
			[1.74]	[1.78]
Constant	10.16	11.15	-0.369	-0.068
	[7.38]	[11.4]	[1.48]	[0.53]
Adj. R^2	0.831	0.855	0.770	0.761

NOTE: Sample period 2003:Q2–2011:Q3. Each specification also includes the dependent variable in the previous quarter. In some regressions we also add the term spread variable and dummy for the Second Lebanon war (not reported). t-statistics are reported in brackets.

Table 3. Banking indicators affecting the *EBP With SH*

Explanatory variable	*(1)*	*(2)*	*(3)*	*(4)*
CDS_Isr	0.002 [3.66]	0.002 [2.91]		0.001 [2.43]
***gLLR*(-1)**		55.66 [1.63]	57.57 [2.01]	56.99 [1.63]
***sLLR*(-1)**	19.84 [3.96]	25.48 [4.36]	22.94 [4.27]	25.88 [4.25]
***Int_gap*(-1)**			1.924 [3.79]	
***credit_gr*(-2)**	0.548 [2.18]	0.598 [2.52]	0.516 [2.41]	0.581 [2.39]
***SH*(-2)**	-0.16 [2.37]	-0.07 [2.95]	-0.08 [1.23]	-0.18 [2.75]
Adj.R^2	0.636	0.675	0.743	0.662
No. Obs.	27	27	27	27

t-statistics are reported in brackets.

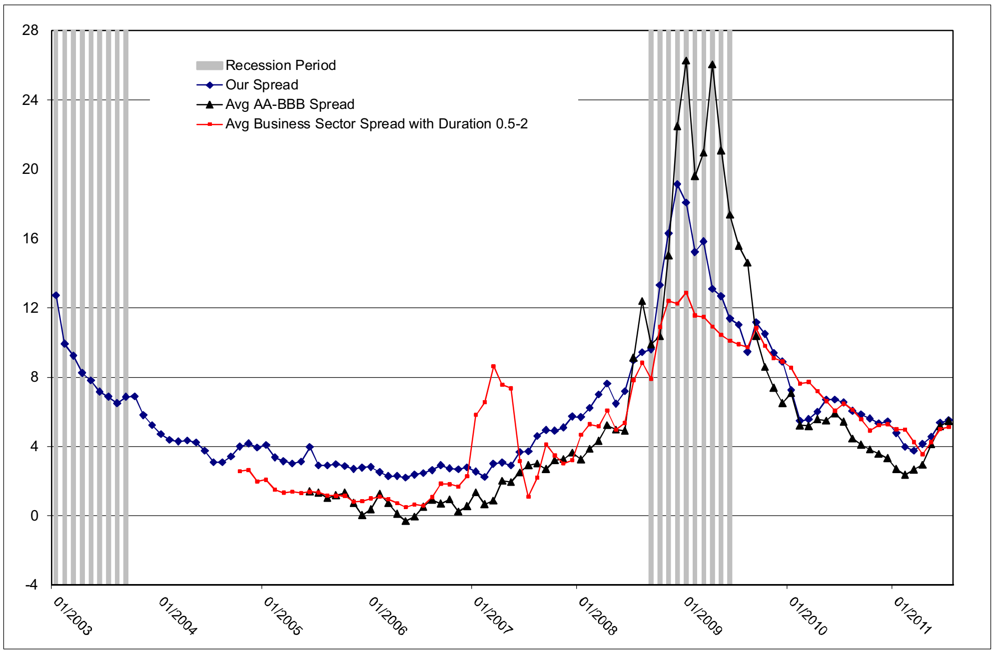
Table 3a. Banking indicators affecting the *EBP where SHr is used*

Explanatory variable	*(1)*	*(2)*	*(3)*	*(4)*
CDS_Isr	0.023 [3.31]	0.018 [3.01]		0.017 [2.12]
***gLLR*(-1)**		52.98 [1.39]	57.29 [2.04]	57.03 [1.60]
***sLLR*(-1)**	17.42 [3.69]	21.04 [3.46]	19.26 [4.07]	23.16 [3.99]
***Int_gap*(-1)**			2.389 [4.86]	
Credit_gr(-2)	0.487 [1.87]		0.381 [1.84]	0.510 [2.02]
***SHr*(-2)**	-0.05 [2.21]	-0.07 [3.02]	0.01 [1.19]	-0.06 [2.59]
Adj. R^2	0.627	0.603	0.661	0.652
No. Obs.	27	27	27	27

t-statistics are reported in brackets.

Figures:

Figure 1. Selected Corporate Credit Spreads



Note: Sample period 2003.1–2011.7. The figure depicts the following credit spreads: our spread; Bbb–Aa rated corporate bond spreads; Business sector corporate vs. government bonds with duration ranging 0.5–2 years.

Figure 2. Weighted Average Distance to Default

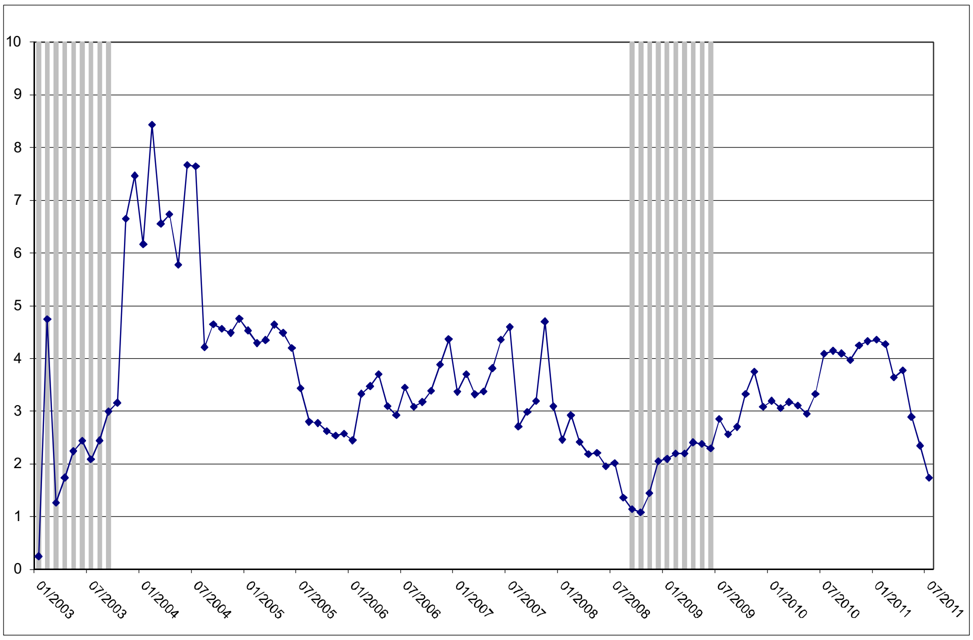


Figure 3. Implications of a shock to *sLLR* on banks' conduct and on the EBP

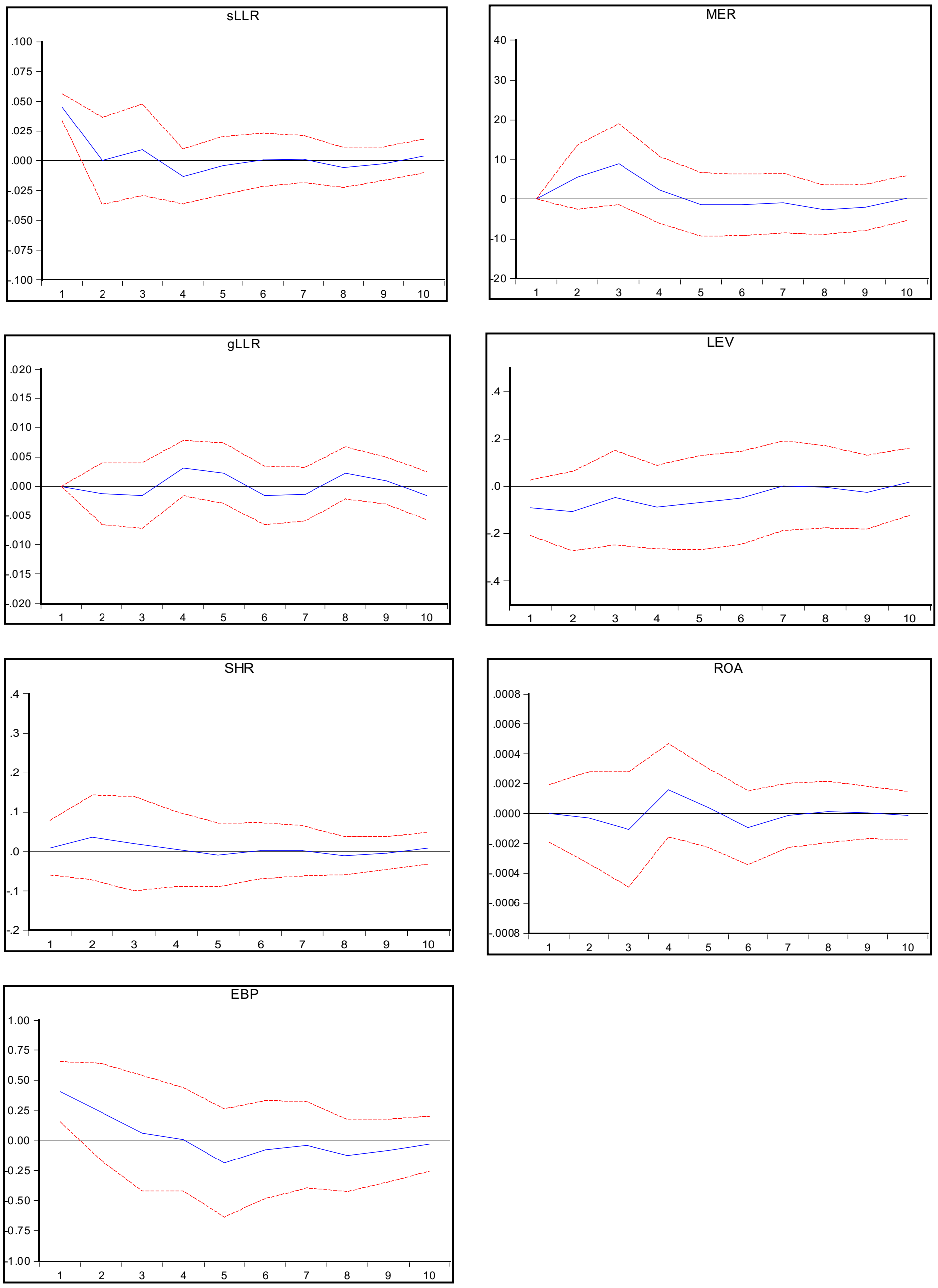


Figure 4. Implications of a shock to CAP on banks' conduct and on the EBP

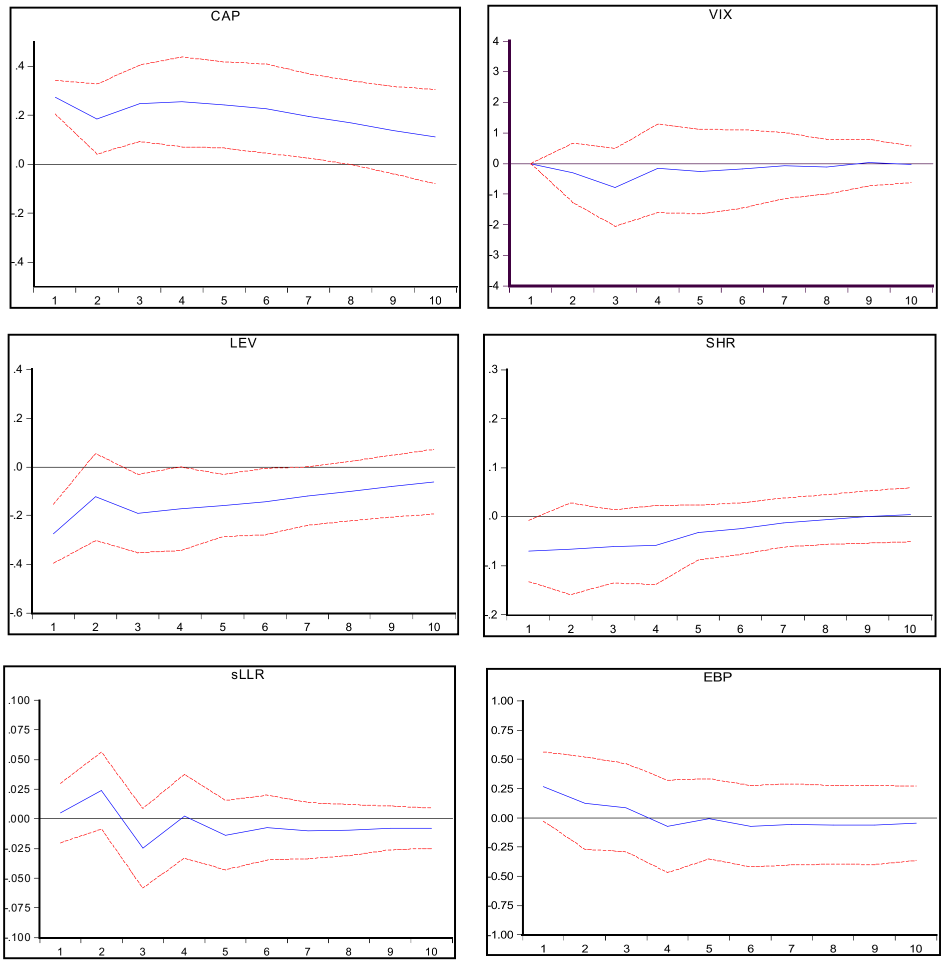


Figure 5. Implications of a shock to *COV* on banks' conduct and on the *EBP*