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CONTAGION AND CORRELATION IN EMPIRICAL MODELS OF BANK CREDIT RISK IN ISRAEL

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Abstract

We apply a methodology for analyzing bank credit risk in Israel, which distinguishes between contagion and correlation on the one hand, and risk factors that are macroeconomic, sectoral and idiosyncratic on the other. Credit risk may be correlated because the observed and unobserved drivers of credit risk happen to be correlated, or because they are causally related through contagion. Bank credit risk is measured by the proportion of problem loans in credit sectors of Israel's banking system. Contagion is malignant and infectious if credit risk in one sector increases credit risk in other sectors. Contagion is benign and immunizing if credit risk in one sector reduces credit risk in other sectors. In some sectors, such as construction, credit risk is highly contagious and malign. On the other hand, credit risk elsewhere immunizes credit risk in the construction sector through benign contagion. According to our results there are two aspects related to the construction sector. First, construction is greatly over-represented in bank credit risk. Second, credit risk in construction is highly contagious relative to other sectors. By contrast, our results suggest that the growth in mortgages is unlikely to be a major problem if monetary policy is normalized: Credit risk among persons is less contagious than among construction companies. In some sectors, such as hospitality, credit risk is not contagious but is highly volatile. Although contagion increases volatility, it makes little difference to the correlation between bank credit risks because benign and malignant contagion offset each other. This systemic methodology may be used by banks for stress-testing and in fulfillment of their obligations under Basel III.

Keywords: contagion, correlated risk, bank credit risk, volatility

Contagion: "The communication of disease from body to body by contact direct or mediate." *Shorter Oxford English Dictionary*

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1. INTRODUCTION

Israel has been fortunate in having a stable bank system at a time when banking systems elsewhere have undergone severe strain and instability. In this paper we use data for Israel to investigate the determinants of bank credit risk, which constitutes a key parameter in the stability of the banking sector as a whole. Banks in Israel and elsewhere are required under Basel II and III to undertake stress testing to determine their exposure to credit risk. The statistical models that they use for these purposes are estimated using proprietary data for individual customers. We argue that in such customer-based models of credit risk it is difficult to identify systemic risk, which has been recognized, especially since 2007, as a major factor in the propagation of financial instability. Systemic risk involves the functioning of the banking system as a whole, including correlation and contagion in credit risk, as we discuss below. In customer-based credit risk models, it is methodologically difficult to see the systemic forest for the individual trees (customers).

In this paper we propose a methodological alternative to customer-based credit risk models, which sets as its main goal the estimation of systemic risk phenomena including contagion and correlation in the proliferation of bank credit risk. Our model uses data on credit risk by economic sectors rather than individual customers. This higher level of aggregation makes it easier to identify the systemic forest from the trees. The methodology we propose decomposes bank credit risk into contagious components, correlated components and idiosyncratic components. We show that some sectors are more contagious than others. For example, credit risk in the construction sector is highly contagious; it spreads to other sectors, and across the banking system as a whole.

We show that contagion induces correlation in credit risk. However, credit risk might be correlated for reasons unrelated to contagion. It is a methodological challenge to winnow contagion from the chaff of correlation. Indeed, an important contribution concerns the econometric identification of contagion. We also identify macroeconomic and sectoral factors that drive credit risk.

Recent reports by the Supervisor of Banks have been rightly upbeat over bank credit risk in Israel. Credit delinquency, which declined in the 2000s, has continued to decline up to 2016. The main fear is about mortgage credit risk. The share of mortgages and housing finance in bank credit has doubled since 2000. In the past, delinquency rates in housing credit were the lowest among all credit sectors. The fear is that if the Bank of Israel normalizes interest rates by ending its “zero” interest policy mortgage borrowers will be caught between higher costs of borrowing and falling house prices. Our results suggest that this prospect is improbable. More important is the effect of normalization on credit risk among building contractors than among mortgage borrowers. Indeed, our results indicate that not only is credit risk in the construction sector the most severe, it is also most contagious.

a. Literature Review

Studies of financial contagion fall into two broad groups, "statistical" and "structural". The first, dating back to King and Wadhwani (1990), searches for breaks or nonlinearities in correlated time series models, and defines contagion if cross-market comovements increase significantly in turbulent times.[1] Refinements to this approach have been proposed by Forbes and Rigobon (2002) and Bae et al. (2003). Pericoli and Sbracia (2003) and Dungey et al. (2005) have usefully reviewed the statistical approach. Other statistical approaches attribute to contagion what cannot be attributed to observable fundamentals (Connolly and Wang 2003, Milunavitch and Tan 2013), or attribute to contagion statistical frailty (Duffie et al., 2009, Chou 2012) as defined by unobservable common factors in default models.

These statistical definitions of contagion differ from the epidemiological concept of contagion. Epidemiological theories[2] specify the causal mechanism through which disease spreads among a population made up of infectives, susceptibles and immunes. Disease may spread through contagion because the germs of infectives are transmitted to susceptibles, or it may spread through heterogeneity in susceptibility so that the most susceptible are the first to succumb to a common health hazard, and the least susceptible are the last. In the former case, there is a causal effect of infectives on susceptibles, but not in the latter case. In both cases, however, the disease spreads among the population. In both cases health status is correlated, but its causes are very different, as are the policy implications. Quarantine will halt the spread of contagious disease, but it will make no difference to the spread of non-contagious diseases. In the latter case, health authorities must eliminate the common health hazard or immunize the population to prevent the spread of the disease.

Structural theories of financial contagion are more closely related to epidemiology because they evince the causal mechanisms through which contagion propagates. Allen and Gale (2000), Giesecke and Weber (2004), Egloff et al. (2007) and Horst (2007) distinguish between correlation induced by common risk factors, such as the business cycle, and correlation induced by contagion, such as through counterparty risk and liquidity shocks. The former correlation is circumstantial while the latter is causal. With the exception of Jorion and Zhang (2009), who show that bankruptcies induce contagion via counterparty risk, absence of data has inhibited empirical research on structural contagion. Lando and Nielsen (2010) investigate “contagion through covariates”, where firm level default intensities depend on the covariates of other firms. However, they admit (p. 370) that the predictive power in these covariates may not be causal.

Our purpose in this paper is fourfold, the first three of which are of general theoretical and methodological interest, while the fourth is of specific relevance to bank credit risk in Israel, and the Bank of Israel’s policy for handling these risks. First, we emphasize the differences between structural and statistical contagion on the one hand, and

[1] See also Rodriguez (2007) and Cheng et al. (2012) on copula models, and Min and Hwang (2012) on increased correlation.

[2] See Daley and Gani (1999) for an introduction and review of epidemiological theory and modeling.

epidemiological and financial contagion on the other. Second, we propose an econometric methodology to distinguish and identify contagion, which is causal, from correlation, which is not. Third, whereas most studies measure credit risk indirectly through asset price data under the assumption that the market correctly prices risk premia, we use direct measures of bank credit risk. Fourth, since the empirical application is for Israel, we shed light on the causes of credit risk in the banking sector in Israel, we assess future prospects for bank credit risk, especially as far as housing finance is concerned, and we critically assess the credit risk policy of the Bank of Israel.

Econometric identification of contagion may be understood in terms of the Reflection Problem (Manski 1995), which distinguishes between correlated, contextual and endogenous effects. The former are induced by correlated unobservable shocks between sectors. Contextual effects are induced by common observable factors. Endogenous effects arise when there is a causal effect of credit risk on other credit risks. Endogenous effects and contagion are synonymous.

The econometric identification of endogenous effects is problematic notwithstanding the specification of contextual and correlated effects. Identification of causal effects between infectives and susceptibles requires instrumental variables affecting the former but not the latter. If, however, contagion takes time, matters are simplified. To identify the causal effect of infectives on susceptibles, we simply require that their outcomes at time t-1 be weakly exogenous[3] with respect to susceptibles' outcomes at time t. Exploiting the principle of weak exogeneity, the correlation in bank credit risk between economic sectors may be decomposed into correlated, contextual and endogenous (contagious) effects. We illustrate the methodology using data on bank credit risk in Israel.

Although micro data are not published on bank credit risk for reasons of confidentiality, many central banks[4] and regulatory authorities publish aggregated data on bank credit risk for individual banks or for the banking system as a whole. To the best of our knowledge, such data have not been used before to shed light on credit risk and its determinants. We therefore use data published by the Bank of Israel to estimate empirical models of bank credit risk in which contagion occurs between economic sectors rather than between counterparties or firms. Adverse shocks are hypothesized to transmit themselves between different sectors of the economy through vertical and horizontal linkages between them.

[3] Engle, Hendry and Richard (1983). If Y_t depends on X_{t-1} and X_t depends on Y_{t-1}, X_{t-1} is weakly exogenous if the residuals of the models for Y_t and X_t are serially independent. If X_{t-1} is not weakly exogenous the relationship between Y and X would be merely Granger-causal.

[4] Such as the Federal Reserve, the Bank of England, the Reserve Bank of Australia and the Bank of Italy. Our approach therefore has broad applicability.

2. THEORY AND METHODS

a. Contagion

Let y_t denote the vector of credit risk in sector n = 1,2,…N at time t, and let Θ denote an NxN matrix of intersectoral credit relationships with elements θ_{nj}, which is zero along the leading diagonal and between immune sectors. Since contagion may not be mutual, θ_{nj} may be zero when θ_{jn} is positive. We assume that contagion takes time, i.e. one period.[5] We propose a simple first-order VAR-X model of credit risk:

$$(1) \quad y_t = \alpha + \Theta y_{t-1} + \Lambda y_{t-1} + Bx_t + \Phi z_t + u_t$$

where α is an N-vector of fixed effects, x is a K-vector of sector specific variables, B denotes an NxK coefficient matrix of loadings with $\beta_{nk} = 0$ for variables that do not apply to sector n, and z is an H-vector of macroeconomic variables where Φ denotes an NxH matrix of macroeconomic loadings ϕ_{nh}. Whereas B is naturally a sparse matrix because x_k may only affect one or two sectors, Φ is not sparse because most if not all credit risks depend on the macroeconomic factors. Λ is a diagonal matrix of inertial coefficients where λ_n is the autoregressive coefficient between credit risk in sector n at time t and at time t-1. Finally, u is a vector of sectoral credit risk shocks, with variance-covariance matrix Σ_u. If Σ_u is diagonal, these shocks are independent across sectors. If it is not diagonal, this constitutes an additional source of credit risk correlation.[6]

Dungey et al. (2005) define statistical contagion in terms of Σ_u, which measures correlation among the unobserved components of credit risk, and does not have a causal interpretation. By contrast, we define contagion in terms of Θ since it is through Θ that credit risk propagates causally from infectives to susceptibles.

The general solution to Equation (1) is:

$$(2) \quad y_t = (I_N - \Theta - \Lambda)^{-1}\alpha + \sum_{i=0}^{t}(\Theta + \Lambda)^i\left(Bx_{t-i} + \Phi z_{t-i} + u_{t-i}\right) + Ar^t$$

where r denotes the vector of N eigenvalues of $I_N - (\Theta + \Lambda)L$, A is the matrix of arbitrary constants obtained from the initial conditions, and L is a lag operator. Stationarity requires that these eigenvalues lie within the unit circle. Equation (2) defines the propagation mechanism of credit risk between sectors and over time. The impact multipliers are simply $Bx_t + \Phi z_t + u_t$, but the higher order impulse responses depend on Θ and Λ. Contagion causes credit risk shocks to spillover onto other sectors, since the coefficient matrix of u_{t-i} is

[5] In Appendix 2 we show that if contagion is also instantaneous the methodology identifies contagion. However, the instantaneous and lagged contagion effects cannot be separately identified.

[6] Because credit risk cannot be negative, Equation (1) is in principle nonlinear. If y is a logistic function of credit risk (log odds default ratio) the non-negativity of credit risk is ensured. We use this transformation below.

$(\Theta + \Lambda)^i$. In the absence of inertia ($\Lambda = 0$), this coefficient is simply Θ^i; it depends entirely on contagion. The same applies to sectoral and macroeconomic shocks.

From Equation (1) the unconditional variance-covariance matrix of credit risk may be obtained[7]:

$$
\begin{aligned}
&\Sigma_y = E(yy') = \Sigma_{yx} + \Sigma_{yz} + \Sigma_{yu} \\
&\Sigma_{yx} = [I-(\Theta+\Lambda)]^{-1} B\Sigma_x B' [I-(\Theta'+\Lambda')]^{-1} \\
(3)\quad &\Sigma_{yz} = [I-(\Theta+\Lambda)]^{-1} \Phi\Sigma_z \Phi' [I-(\Theta'+\Lambda')]^{-1} \\
&\Sigma_{yu} = [I-(\Theta+\Lambda)]^{-1} \Sigma_u [I-(\Theta'+\Lambda')]^{-1}
\end{aligned}
$$

Equation (3) shows that the unconditional covariance matrix of credit risks may be decomposed into three components. The first (Σ_{yx}) is the component induced by the covariance matrix of sectoral credit risk factors (Σ_x), which is assumed here to be homoscedastic. The second (Σ_{yz}) is the cyclical or macroeconomic component, where Σ_z denotes the covariance matrix for the macroeconomic variables. Finally, Σ_{yu} is the contribution of idiosyncratic credit risk shocks, where Σ_u has already been discussed. Having estimated Θ, Φ, Λ, B, Σ_x, Σ_z and Σ_u, we may use Equation (3) to decompose the covariance matrix of credit risk into its three component parts.

The θ coefficients have a causal interpretation provided y_{t-1} is weakly exogenous in Equation (1). It would not be weakly exogenous if u was autocorrelated, because in this case y_{t-1} and u_t are generally not independent. In this case the θ coefficients would estimate Granger-causality, which is about predictability or sequencing, but they do not identify contagion. Granger-causality is a necessary, but not sufficient, condition for contagion.[8] Contagion also requires that y_{t-1} be weakly exogenous for Θ.

Since absence of serially correlated errors induces weak exogeneity, we use the Lagrange multiplier (LM) statistic for VAR innovations to determine whether the innovations are serially independent within, as well as between, sectors. The LM statistic is unbiased in the presence of lagged endogenous variables such as y_{t-1}, and it is conditioned on the state variables (x, z) used to estimate the model. Serial correlation may be artificially induced by dynamic misspecification (Hendry 1995). For example, the innovations of a first-order VAR might be serially correlated when they are serially independent in a second-order VAR. A common factor test (Mizon 1995) may be used to choose between these VAR models. Because dynamic specification and weak exogeneity cannot be separated, we attach major importance to the former.

[7] For simplicity we ignore covariance terms between x and z.

[8] Longstaff (2010) estimates a VAR model to show that CDO risk Granger-causes stock and Treasury returns. This would be evidence of contagion if the VAR innovations were serially independent.

Despite the fact that Equation (1) is only first-order, it may be difficult to interpret the components of Equation (3). In an appendix, we therefore provide a simple symmetric first-order model in which there are only two sectors (N = 2), there is only one macro credit risk factor, and there are no sector specific factors. Hence, θ denotes the coefficient of contagion, λ denotes the coefficient of inertia, ϕ denotes the coefficient of credit risk to the macro factor, and ρ denotes the correlation between u in the two sectors.

Table 1 illustrates the effect of these structural parameters on the correlation in credit risk between the two sectors (r), and the volatility in credit risk (var(Y)). Case 1 in Table 1 serves as a baseline in which all structural parameters are zero, so that the correlation in credit risk is zero and its volatility, as measured by the variance, is 1. Case 2 shows that if credit risk is anticyclical (ϕ = -1), the correlation in credit risk increases from zero to one-half and volatility doubles. Case 3 retains the assumptions of Case 2, but allows for inertia or persistence in credit risk (λ = 0.3). The correlation remains unchanged, but volatility increases. Case 4 retains the assumptions of Case 3, but allows for credit risk shocks to be correlated (ρ = 0.2). Volatility remains unchanged, but the correlation in credit risk increases from 0.5 to 0.6.

Table 1
Determinants of the Correlation and Volatility in Credit Risk

Case	θ	λ	ϕ	ρ	r	Var(Y)
1	0	0	0	0	0	1
2	0	0	-1	0	0.5	2
3	0	0.3	-1	0	0.5	2.453
4	0	0.3	-1	0.2	0.6	2.453
5	0.2	0.3	-1	0.2	0.685	2.841
6	0.2	0.3	-1.2	0.2	0.714	3.139

$\sigma = \sigma_z = 1$

Thus far the coefficient of contagion has been zero. Therefore, the correlation in credit risk was induced by the business cycle and correlated shocks. Case 5 retains the assumptions of Case 4, but allows for contagion (θ = 0.2). The correlation in credit risk increases from 0.6 to 0.685, and volatility increases too. Finally, Case 6 shows that if credit risk is more anti-cyclical, volatility increases and credit risk becomes more correlated.

b. Epidemiology vs. Financial Contagion

The analogy between infectious disease and financial contagion is, of course, imperfect. In insurance markets, negative shocks to the insured transmit themselves to insurers, thereby inducing contagion in the epidemiological sense. In the absence of insurance markets, such negative shocks would be self-limiting and therefore not contagious. Since insurance is welfare improving, contagion is an inevitable and desirable consequence of risk pooling.

There is no epidemiological counterpart to insurance-induced contagion. This makes financial contagion conceptually different to epidemiological contagion. Ideally, it would be desirable to decompose contagion in credit risk into insurance-induced contagion and contagion unrelated to insurance. Our inability to do so limits the policy implications of our analysis, since contagion unrelated to insurance is an expression of market failure. Instead, our analysis focuses on the drivers of credit risk and its propagation. We return to this issue in our concluding section.

Apart from insurance-induced contagion, contagion in credit risk has many facets. Let A be an infective and B a susceptible. If A supplies inputs to B, B's business might be disrupted. If A owes money to B, e.g. because of trade credit, contagion will be adverse. Jorion and Zhang (2007) note that contagion may be "good" as well as "bad". In the latter case, θ is positive so that there is positive feedback between credit risks. In the former case, θ is negative. For example, if A and B are rivals, A's credit risk might benefit B's business, thereby reducing B's credit risk. One man's misfortune is another man's blessing. Alternatively, there may be a signaling or demonstration effect such that A's credit risk might induce B to be more cautious. In epidemiology, contagion is negative when B's immunity increases as result of B's exposure to A's disease. More generally, just as market risk may be positive or negative, so might contagion be positive or negative.

In our empirical application, the data refer to economic sectors rather than individuals or companies. Insurance-induced contagion is less likely to apply to economic sectors, since there is no formal insurance between economic sectors. Because economic sectors are related through input-output, it might be expected that contagion must be bad, i.e. θ should be positive. For example, the financial difficulties of suppliers in one sector might disrupt business in other sectors. Also, competition between sectors is expected to be weaker than competition within sectors. On the other hand, if suppliers respond to their financial difficulties by improving efficiency, this will benefit sectors that purchase their inputs. In summary, contagion may be malignant or benign. Whether θ is positive or negative, or whether it is large or small are empirical matters, which we investigate below.

c. Empirical Methodology

In view of the substantial heterogeneity between sectors, we do not treat our data as panel data. We therefore estimate individual models for each sector. This is feasible because the data are available on a quarterly basis from 1997:Q1 to 2010:Q3. Let Y_{nt} represent an appropriate measure of bank credit risk in credit sector n at time t, where the N sectors are defined in terms of different types of business (industry, services, persons, etc). The z-factors are aliased by h = 1,2,..,H and the x-factors are aliased by k = 1,2,..,K.

In Section 2.1 the dynamics were restricted to first order for expositional purposes. Inertia was first order, contagion occurred after one period, and the sectoral and macroeconomic risk factors affected credit risk instantaneously. In practice, inertia may be greater than first order, contagion might take longer than one period, and the risk factors might not affect credit risk instantaneously. Indeed, these dynamics have to be estimated from the data. We estimate the parameters of the model (λ's, β's, and θ's) using the following VAR-X model:

$$y_{nt} = \alpha_n + \sum_{i=1}^{p} \lambda_{ni} y_{nt-i} + \sum_{h=1}^{H} \sum_{i=0}^{b} \phi_{nhi} z_{ht-i} + \sum_{k=1}^{K} \sum_{i=0}^{d} \beta_{nki} x_{nkt-i} + \sum_{j \neq n}^{J} \sum_{i=1}^{c} \theta_{nji} y_{jt-i} + u_{nt} \tag{4}$$

In Equation (4), the λ coefficients capture inertia in bank credit risk, the ϕ coefficients capture the dynamic effect of the systemic risk factors such as the business cycle, and the β coefficients capture the dynamic effects of the sectoral risk factors on bank credit risk. The θ coefficients capture contagion. Finally, u_{nt} is a residual that may be correlated between sectors. If it is autocorrelated, Y_{nt-i} and Y_{jt-i} would not be weakly exogenous for the λs and the θs.

The lag orders for Y_n and Y_j are from 1 to p and 1 to c respectively. The lag orders for z and x are from 0 to b and 0 to d respectively. As explained below, these lag orders are determined on empirical grounds. In practice (see Table 5), some lag orders for z and x do not commence at 0. For lag orders that commence at 0, z and x must be weakly exogenous. Shocks to z and x propagate within and between sectors of the market for bank credit. X-shocks, which directly affect one sector, will propagate onto other sectors via the θ coefficients. Z-shocks, which directly affect more than one sector, will propagate both within and between sectors inducing "domino" and "boomerang" contagion. Domino contagion occurs when credit risk in Sector n spreads to Sector j and thence to other sectors. Boomerang contagion occurs when credit risk in Sector n rebounds back onto Sector n from Sector j or third sectors. In Section 4 we simulate shocks to the z and x variables using the estimated model.

Identification of the model through weak exogeneity requires that u_{nt} be serially independent within and between sectors, otherwise the lagged dependent variables in Equation (4) may not be weakly exogenous. Identification also requires that z_t and x_t be weakly exogenous, which requires that innovations in credit risk do not immediately affect the current state of the economy. If z and x are directly affected by credit risk, they would not be weakly exogenous. If, however, credit risk has a lagged effect on z and x, they may be weakly exogenous. Some of the risk factors are strongly exogenous because they refer to variables, such as the price of oil, which are determined abroad.

Estimation of the model proceeds as follows. Equation (4) is estimated by sector, providing estimates of λ, β, ϕ, and θ. The estimates of u_{nt} are then used to check for common unobserved factors. If these residuals are correlated between sectors and serially correlated, we would use dynamic factor analysis (Stock and Watson 1988) to estimate the unobserved factors from the residuals. If, instead, the residuals are serially independent but correlated between sectors, we would use static factor analysis to estimate the unobserved risk factors and their loadings. Finally, if the residuals are serially independent and are not correlated between sectors, there are no unobserved factors.

The lag lengths p, b, c and d are determined using the “general-to-specific” methodology of dynamic specification (Hendry 1995). Hypotheses about the risk factors are discussed in the next section. Misspecification checks are used to guard against the risk of data-mining. These include various LM tests as well as forecasting tests. The latter are particularly important since data-mined models typically forecast badly. We test the data for stationarity. If credit risk is trending, it cannot be stationary. It might be argued that since credit risk is naturally bounded between zero and one, it must be inherently stationary. However, if credit risk is sufficiently persistent, it may behave like a driftless random walk, in which event it is nonstationary. Indeed, in some sectors credit risk turns out to be nonstationary.

3. THE DATA

a. Defining Bank Credit Risk

In the case of bank credit risk, confidentiality prevents the publication of information on individual customers. These proprietary data are no doubt analyzed by the banks themselves[9] and individual customers are profiled in terms of their credit risk. However, the results naturally remain unpublished. As noted by Dermine and de Carvalho (2005), data scarcity explains why empirical studies of bank credit risk are rare.

Since 1997, the Bank of Israel has published quarterly data on loan-loss provisions (write-offs) and problematic credit (delinquent credit) for Israel's five main banking groups.[10] These data refer to total credit and unfortunately do not distinguish between different sectors of the credit market. However, the Bank of Israel also publishes data on loan-loss provisions and problematic credit for different sectors of the credit market for the banking system as a whole. These latter data show that there is extensive heterogeneity in problematic credit by sector. We use these data to estimate Equation (4) for the banking system as a whole.

Problematic credit is defined by the Bank of Israel as including loans that are non-performing, are in temporary arrears, are under special supervision, are due to be rescheduled, or have been rescheduled. This definition of problematic credit is broader than its counterpart at the Federal Deposit Insurance Corporation (FDIC), where the definition consists of non-performing loans and impaired loans. The FDIC definition is roughly comparable to the first two components of the Bank of Israel definition (non-performing and in temporary arrears). However, it is difficult to compare problematic credit in Israel,

[9] Indeed, banks are required to undertake such exercises under the terms of "Basel III".
[10] Bank Hapoalim, Bank Leumi, First International Bank, Discount Bank and United Mizrahi Bank. Smaller banks such as Bank Yahav are included in these groups.

where until recently there was no swap market, with problematic credit elsewhere because Israeli banks could not off-load problematic credit in the credit swap market. This means that problematic credit in Israel may appear high because it remains on the balance sheet until it is written-off or ceases to be problematic.

An even narrower measure of problematic credit would be loan-loss provisions. These provisions are a formal accounting item that is included in the banks' profit and loss statements. Typically, write-offs lag behind credit risk because banks only make loan-loss provisions after it has become clear that the loans are beyond rehabilitation. Even then, there may be accounting reasons in determining when to declare write-offs.

Figure 1
Loan-loss Provisions as a Percentage of Problematic Credit

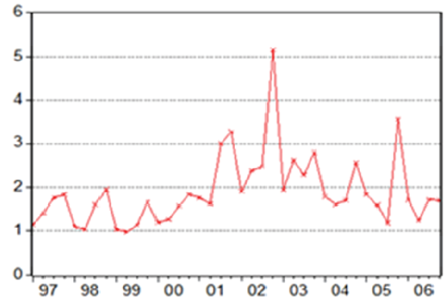


Figure 1 plots the ratio of write-offs to problematic credit for the Israeli banking system. Loan-loss provisions as a share of problematic credit typically varies between 1 percent and 3 percent per quarter, but peaked at 5 percent in 2002. It is also seasonal—lowest in the first quarter and highest in the last—reflecting the fact that the tax year ends with the calendar year. There also seems to be a cyclical component to the rate of loan-loss provisions. There was a deep recession that began in the second half of 2000 and reached its trough in 2002, and the economy began to recover in 2004. Incomplete data for 2007–2010 show that during the recession of 2008 the rate of write-offs increased but subsequently returned to 1–2 percent following the economic recovery. During the recession, the rate of loan-loss provisions was about 1 percentage point higher. One naturally expects loan-loss provisions to vary directly with problematic credit, and they do. However, the timing of declaring loan-loss provisions seems rather haphazard.[11] In 2015 the ratio of write-offs to problematic credit was 1.6 percent.

[11] Hess (2007) also notes that in Australia, write-offs are poorly correlated with problematic loans.

b. Problematic Credit

Table 2
The Sectoral Composition of Bank Credit and Credit Risk
(percent)

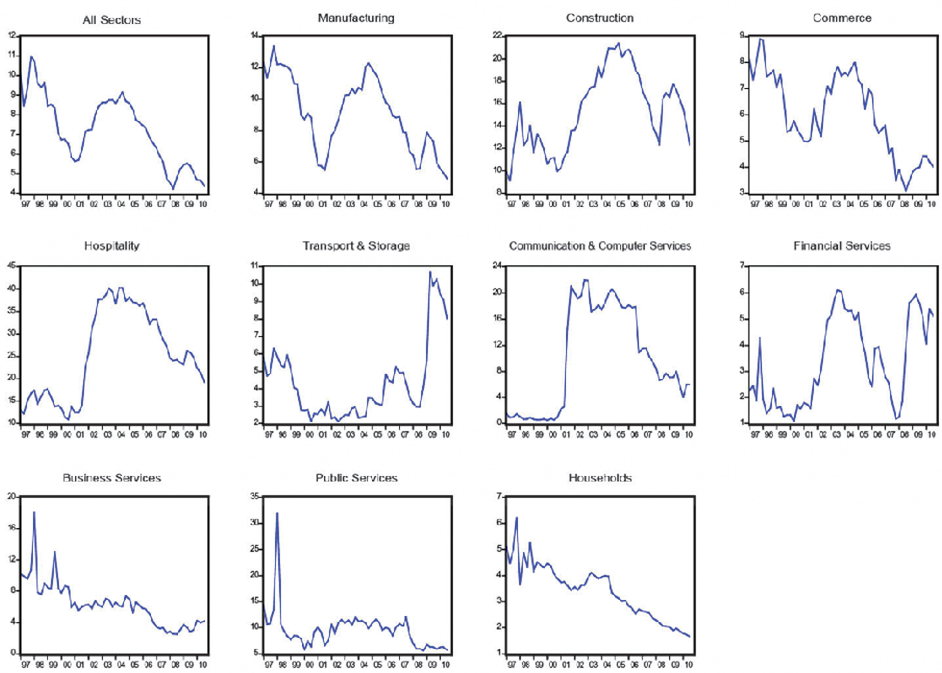
	1997		2003		2010		2011
	Credit	Problematic Credit	Credit	Problematic Credit	Credit	Problematic Credit	Share of value added[a]
Manufacturing	14.9	18.1	15.5	18.3	12.1	13.7	22.8
Construction	20.8	25.9	13.3	29.4	11.7	33.1	6.0
Commerce	7.4	6.0	7.6	6.5	6.0	5.5	14.0
Hospitality	2.1	3.2	2.1	9.3	1.3	5.8	2.9
Transport & Storage	2.3	1.3	2.5	0.9	2.1	3.8	5.5
Communications & Computer services	1.7	0.2	4.0	8.4	2.4	3.3	9.8
Financial services	4.7	1.8	9.0	6.2	11.0	12.9	8.9
Business services	3.6	3.5	3.7	2.5	4.1	3.9	18.7
Public services	1.8	2.2	1.7	2.4	1.3	1.7	3.9
Households	27.9	15.8	30.3	13.4	38.7	14.9	57.8[b]
Agriculture, electricity and water	12.8	21.8	10.2	2.6	9.4	1.6	4.5

a. Shares sum to 97 percent, excluding "households", due to omitted items.
b. Consumption as a share of GDP.

Table 2 shows the sectoral composition of bank lending as measured by outstanding credit and these sectors' shares of problematic credit. The largest sectors are households (including mortgages), construction and manufacturing. The most heavily leveraged sector is construction, which accounted for 11.7 percent of bank credit in 2010 despite its relatively small share of value added. It also had the highest share of problematic credit. There have been two major changes in the sectoral composition of bank credit. Financial services have grown in importance, and so have households. Indeed, the latter has continued to grow in importance since 2010. The construction sector is vastly over-represented in problematic credit, while households are under-represented. The substantial over-representation of agriculture in problematic credit in 1997 resulted from the financial crisis in the kibbutzim and moshavim (agricultural cooperatives), which was subsequently solved through legislation and a political settlement.

We define the rate of problematic credit (RPC) as the ratio of problematic credit to the total amount of outstanding credit. RPC measures the ex-post probability that a shekel of bank credit is problematic. The first graph in Figure 2 plots RPC for all sectors. RPC fell from 10 percent in 1997 to 4 percent in 2010 and seems to be anticyclical. RPC fell during the dot.com boom at the end of the 1990s, increased during the recession of 2000 – 2004, fell during the subsequent economic recovery, increased during the recession of 2009, and fell with the economic recovery in 2010. However, the subsequent graphs, which plot RPCs for different sectors of the credit market, indicate a substantial degree of heterogeneity. For example, the last two graphs show that RPC for households and business services has been falling continuously, while in other sectors, such as hospitality (tourism, hotels and restaurants) it has been increasing. In some sectors, such as hospitality and construction, RPC is persistently high while in other sectors, such as transportation and storage, it is low.

Figure 2
Rates of Problematic Credit



In some sectors, such as manufacturing and construction, the rate of problematic credit seems to follow the main trend, while in other sectors, such as households and business services, RPC appears to buck the trend. Since 2010, RPC for all sectors has fallen by 2 percentage points, and by 2015 it was at the lowest level since records began in 1997.

Unit root tests for RPC are shown in Table 3. The augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics in Table 3 indicate that the null hypothesis of the unit root for RPC cannot be rejected, suggesting that RPC is nonstationary in all sectors, i.e. RPC is I(1). The KPSS statistic tests the null hypothesis that RPC is I(0). They indicate that in 5 out of 9 sectors, we cannot reject the hypothesis that RPC is I(0). We therefore specify stationary factors in the five stationary sectors, and we specify nonstationary factors in the four nonstationary sectors. For all sectors we carry out a test for spurious regression as reported below.

Table 3
Unit Root Tests for the Rate of Problematic Credit

	Manufacturing	Construction	Commerce	Hospitality	Transport & Storage	Communications & Computer services	Financial services	Business services	Households
ADF	-1.47	-1.22	-2.07	-1.90	-1.72	-1.67	-2.08	-3.67	0.36
PP	-1.28	-1.90	-1.42	-1.47	-1.55	-1.49	-1.90	-2.77	-1.27
KPSS	0.47	0.54	0.62	0.49	0.38	0.39	0.44	1.02	1.13

Notes: For ADF and PP the null hypothesis is a unit root. For KPSS the null hypothesis is no unit root. ADF is the 4^{th} order augmented Dickey-Fuller statistic and PP is the Phillips-Perron statistic with a bandwidth of 1–4 with critical value of -2.9 at p = 0.05. KPSS is the 5^{th} order KPSS statistic with critical value of 0.463. The results in Table 3 are robust with respect to lag length selection (Ng and Perron 2001).

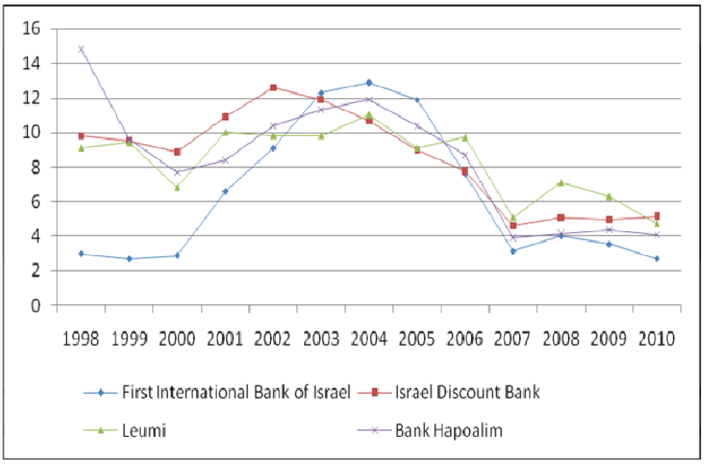
The correlation matrix (Table 4) for sectoral RPCs contains positive as well as a substantial number of negative correlations. The correlations range between 0.9 and -0.38 and in only a few cases are the correlations close to zero.

Table 4
Correlation Matrix for the Rate of Problem Credit

	Manufacturing	Construction	Commerce	Hospitality	Transport & Storage	Communications & Computer services	Financial services	Business services
Construction	0.23							
Commerce	0.90	0.15						
Hospitality	0.17	0.89	0.16					
Transport & Storage	-0.16	0.00	-0.24	-0.20				
Communications & Computer services	0.05	0.74	0.13	0.89	-0.37			
Financial services	0.01	0.65	0.03	0.65	0.25	0.53		
Business services	0.66	-0.27	0.74	-0.36	-0.15	-0.32	-0.32	
Households	0.70	-0.37	0.77	-0.31	-0.38	-0.24	-0.34	0.74

Finally, Figure 3 plots the RPCs of four banks. It shows that RPC varies by bank, but typically falls within the range of 8 to 13 percent. In the late 1990s, the RPC for Bank Hapoalim, which is Israel's largest bank, was relatively high, and the RPC of the First International Bank of Israel (FIBI) was relatively low. However, by 2002 FIBI had converged to the mean. In 2015 RPC was 3.14 percent for Bank Leumi, 3.43 percent for Bank Hapoalim, 3.54 percent for Bank Discount, and 2.39 percent for FIBI. These rates are almost 2 percentage points lower than in 2010.

Figure 3
Rates of Problematic Credit in the Main Banks



4. EMPIRICAL RESULTS

Our main purpose in this section is to estimate Equation (4) for seven main credit sectors, where y represents the rate of problematic credit (RPC). A large range of economy-wide risk factors (z) is hypothesized, including GDP and its components, unemployment, inflation, exchange rates, interest rates, and more. We also use the Bank of Israel's coincident indicator (CI), which is intended to be correlated with the business cycle. We specify a broad range of sector-specific risk factors (x), which naturally vary between sectors. We use the general-to-specific methodology (Hendry 1995) to determine the dynamic structure of the individual factor models, and the choice of factors is largely determined by their ability to predict credit risk. To guard against over-fitting and data-mining, we apply a range of misspecification checks, including forecast tests and serial correlation tests. The models are estimated using quarterly data from 1997:Q1 to 2010:Q3. We exclude from our analysis credit to the agricultural sector because, as mentioned, this sector has been the subject of legislation. We also exclude small and specialized sectors such as diamonds, electricity and water.

We have briefly mentioned the dilemma regarding the potentially nonstationary nature of the data on RPC during the sample period. In sectors where the rate of problematic credit is trend-free, we use the Hodrick-Prescott filter to detrend factors, such as GDP, which have time trends. In sectors where the rate of problematic credit is I(1), we specify factors that are trending. The alternative would have been to specify credit risk factors that cointegrate with RPC for each of the sectors.

We check for spurious regression in two ways. First, we report unit root tests for the "long-run" residuals (u*) derived from the static counterparts of Equation (4), i.e. when the lag structures are collapsed:

$$u^*_{jt} = y_{jt} - \alpha^*_j - \sum_{k=1}^{K} \phi^*_{kj} z_{kt} - \sum_{n=1}^{N} \beta^*_{nj} x_{nt} - \sum_{h \neq j}^{J} \theta^*_{hj} y_{ht-1}$$

(5)

$$\beta^*_{kj} = \frac{\sum_{i=0}^{b} \beta_{kji}}{1 - \sum_{i=1}^{p} \lambda_{ji}} \quad \phi^*_{nj} = \frac{\sum_{i=0}^{d} \phi_{jni}}{1 - \sum_{i=1}^{p} \lambda_{ji}} \quad \theta^*_{hj} = \frac{\sum_{i=1}^{c} \theta_{hji}}{1 - \sum_{i=1}^{p} \lambda_{ji}}$$

These long-run residuals should be stationary in the absence of spurious regression. Secondly, we carry out unit root tests on the full dynamic simulation (FDS) residuals, which substitute out the lagged contagion terms in Equation (4) in terms of the z and x variables which determine them. Therefore, the second test takes account of contagion, whereas the first does not.

There are about 48 model parameters estimated from 392 data points. In the interests of digestibility, we break down the presentation of these parameters as follows. Tables 5 (5.1–5.7) show the factor models for each sector, i.e. the β and ϕ coefficients of Equation (4). Table 6 shows the estimated coefficients of inertia (λ) in Equation (4), and Table 7 shows the estimated contagion coefficients (θ). Finally, diagnostic statistics are shown in Table 8. These include a Chow forecast test in the period between 2009:Q1 and 2010:Q3, an LM test for up to 4^{th} order autocorrelation within sectors, an LM test for 1^{st} order correlation between sectors, and unit root tests for the long-run residuals and the FDS residuals. Since some of the factors are specified in differences, we use d to denote the order of differencing and s to denote the order of seasonal differencing.

Table 5.1
Estimates of β and ϕ: Manufacturing

	Coefficient	d	s	Lag order	Standard error
Industrial production[a]	-6.76	1	2	1	1.81
Share of electrical equipment in industrial production	-5.28	0	0	4	0.73

Table 5.2
Estimates of β and ϕ: Construction

	Coefficient	d	s	Lag order	Standard error
Construction: gross output[a]	-31.45	1	1	1	4.49
Exchange rate[b]	-9.87	0	0	1	2.58
Consumption per head	-19.05	1	4	0	4.91
Public sector investment	-5.90	1	1	3	1.66

Table 5.3
Estimates of β and ϕ: Commerce

	Coefficient	d	s	Lag order	Standard error
Exchange rate (USD)	3.44	1	1	2	1.55
Gross investment	-1.84	1	1	3	0.80
Inflation	-0.79	1	2	0	0.22
Unemployment rate	0.16	0	0	4	0.05

Table 5.4
Estimates of β and ϕ: Hospitality

	Coefficient	d	s	Lag order	Standard error
Foreign tourism[b]	-3.25	0	0	2	0.91
Domestic tourism[b]	-25.86	0	0	2	6.17
Deaths due to terrorism	0.06	0	0	1	0.01
Real wages[c]	-48.19	1	1	0	9.62

Table 5.5
Estimates of β and ϕ: Transport & Storage

	Coefficient	d	s	Lag order	Standard error
Price of diesel fuel	0.47	0	0	4	0.10
Employment in sector[c]	-0.21	1	0	0	0.04
Wages in sector[c]	0.00	1	3	1	0.00
Gross output in sector[c]	-0.04	0	0	1	0.01
YTM indexed bonds	0.54	1	1	2	0.13
Exports	-3.41	1	3	0	0.79

Table 5.6
Estimates of β and ϕ: Financial Services

	Coefficient	d	s	Lag order	Standard error
Employment in sector[a]	-25.69	1	1	2	5.82
TASE 100[c]	-2.57	0	0	0	0.52

Table 5.7
Estimates of β and ϕ: Households

	Coefficient	d	s	Lag order	Standard error
Interest rate: Bank of Israel	0.18	0	0	2	0.02
Unemployment rate	0.14	0	0	1	0.04
Inflation	0.74	0	0	1	0.22
	0.69			2	0.23

Notes: [a] Logged and HP filtered. [b] Logged. [c] HP filtered. [d] order of differencing. [s] order of seasonal differencing, i.e. $\Delta_s z_t = z_t - z_{t-s}$. The dependent variable is expressed as log[RPC/(1-RPC)].

The variables included in Tables 5 are diverse. In most sectors both sectoral and economy-wide risk factors are present. For example, Table 5.1 indicates that the rate of problematic credit in manufacturing varies inversely with the lag of the 2nd seasonal difference in industrial production and with the 4th lag of the share of electronic equipment in industrial production. Tables 5.2 through 5.7 show the risk factors estimated for the other credit sectors as well as their dynamic structure in terms of lags and levels versus differences. For example, credit risk in construction varies inversely with construction activity. It also varies inversely with the exchange rate since for most of the period housing transactions were conducted in US dollars so that contractors benefited from currency depreciation. Some factors are clearly sectoral, such as the price of diesel fuel in transport and arrivals of foreign tourists in the tourism sector. The macroeconomic factors include unemployment, inflation, consumption, investment, interest rates and the exchange rate. It should also be recalled that some sectoral factors are not independent of the business cycle (see below). For the most part the variables in Tables 5 are lagged, which weakens the argument that there might be reverse causality from credit risk to the state of the economy.

Table 6
Coefficients of Inertia (λ_n)

	Households	Manufacturing	Construction	Commerce	Hospitality	Transport and Storage	Financial services
Coefficient	0.22	0.51	0.88	0.79	0.72	0.83	0.74
Lag order	2	1	1	1	1	1	1

Notes: P-value of coefficients of inertia < 0.025.

Table 6 indicates that there is first order inertia (λ_1 = 0.51) in the rate of problematic credit in manufacturing. Inertia in the rate of problematic credit is pervasive and first order. Inertia is weakest in personal credit and strongest in construction, implying that credit risk dies out quickly for households and slowly for construction. On the other hand, the lag order for households is 2 whereas for all other sectors it is 1. Expressing 0.22 at a quarterly rate implies a coeffcient of inertia of 0.47, which is closer to the other coeffcients in Table

6. Some of these coefficients of inertia appear close to 1, such as construction (0.88). However, the ADF and KPSS statistics for construction (Table 8) are -8.37 and 0.23 respectively, suggesting that the risk factors explain the behavior of credit risk over time, independent of inertia.

Table 7 indicates that there is positive contagion from credit risk in construction, and negative contagion from the change in credit risk in transport and storage. It also shows that the rate of problematic credit is also quite heterogeneous in terms of contagion. There are no immune sectors; all sectors are affected by contagion to a greater or lesser extent. All sectors are affected by contagion from at least two other sectors, and some are affected by three sectors. All sectors are contagious with the exception of the hospitality sector. Credit risk in hospitality does not affect other sectors, but it is affected by credit risk in construction and among households. Contagion is malignant in construction amd among households, but it is benign in commerce, manufacturing and transport. This suggests that credit risk in the former sectors aggravates credit risk in other sectors, whereas credit risk in the latter sectors immunizes other sectors against credit risk, by deflecting credit risk away from those sectors. As in Jorion and Zhang (2007), there is good as well as bad contagion.

Table 7
Coefficients of Contagion (θ_{nj})

	INFECTIVES (j)						
INFECTEDS (n)	Commerce	Manufacturing	Transport And Storage	Construction	Hospitality	Financial Services	Households
Manufacturing			-1.17 Δ (2)	0.19 (1)			
Construction		-0.68 Δ (3)	-0.45(4)			-0.32 Δ_2(1)	
Commerce				0.19 Δ (3)			0.31 Δ (1)
Hospitality				0.56 (2)			1.29 Δ_2(1)
Transport Storage	-0.35 Δ (2)						0.56 (1)
Financial Services		-0.11 (3)	-0.18 Δ (3)	0.07 (4)			
Households			-0.06 (1)	-0.13 Δ (2)		0.14 (2)	

Notes: The Table reads horizontally. P-value of contagion coefficients < 0.025. Δ_s indicates that contagion is in seasonal differences and (p) denotes the lag order of contagion. For example, the infective effect of credit risk for households on credit risk in hospitality is $1.29\Delta_{2yt-1} = 1.29(y_{t-1} - y_{t-3})$.

Because there are no immune sectors and almost all sectors are contagious, boomerang contagion predominates over domino contagion. However, some sectors are more contagious than others. There are several aspects to this. First, the timing of contagion varies inversely with the lag orders in Table 7. For example, in the case of households contagion is rapid (lag order 1) whereas in the case of construction contagion is slower (upto lag order 4). Secondly, the size effects of contagion vary. Third, contagion is less persistent if it is in first differences than in levels. Fourth, sectors with more column entries in Table 7 are more contagious. For example, credit risk in construction affects all sectors apart from transport and storage.

Finally, Table 8 shows misspecification tests for the credit risk model as a whole. These include adjusted R^2, the coefficient of variation of the residuals, the p-value of the LM test statistic for up to 4^{th} order autocorrelation in the residuals (not significant), and the p-value of a forecasting test of the model over the final 6 quarters of the sample (not significant). Finally, the ADF statistic for the long-run residuals (-6.75) and the KPSS statistic for the FDS residuals (0.11) are shown. These statistics do not suggest that the credit risk model for industry is spurious. We also tested for heteroscedasticity (White test) in the residuals and for up to 4^{th} order ARCH in the residuals. In none of the sectors did these tests approach statistical significance. Therefore conditional bank credit risk is homoscedastic and does not display ARCH-type heteroscedasticity.

Table 8
Diagnostics

	Adjusted R^2	Standard error	CV	LM1	LM2	Forecast test	ADF long run residuals	KPSS dynamic simulation residuals
Manufacturing	0.95	0.54	0.06	0.36	0.61	0.67	-6.75	0.11
Construction	0.95	0.76	0.05	0.25	0.08	0.96	-8.37	0.23
Commerce	0.94	0.38	0.06	0.59	0.62	0.90	-7.58	0.15
Hospitality	0.98	1.31	0.05	0.32	0.60	0.36	-8.91	0.23
Transport-Storage	0.95	0.53	0.12	0.08	0.07	0.06	-8.95	0.09
Financial services	0.92	0.48	0.14	0.30	0.22	0.40	-6.38	0.06
Households	0.93	0.27	0.08	0.30	0.20	0.74	-9.99	0.11

Notes: The dependent variable is the RPC, except for households, where it is log{RPC/(1-RPC)}. The standard error is measured in percentage points. LM1: p-value of F statistic of LM test for up to 4^{th} order serial correlation in errors. LM2: p-value of F statistic of LM test for 1^{st} order cross-autocorrelation. Forecast test: p-value of F statistic of Chow forecasting test for 2009:Q1–2010:Q3. CV is the coefficient of variation calculated as the mean of the data. ADF long-run residuals: the Augmented Dickey-Fuller statistic for the residuals in Equation (5). KPSS dynamic simulation residuals: the KPSS statistic for the residuals of a full dynamic simulation for 2000–2010.

Although adjusted R^2 exceeds 0.92, the accuracy of the models should be judged by their standard errors. For example, the standard error of 0.54 in the manufacturing sector should be compared to the rate of problematic credit in the sector, which ranges between 6 and 11 percent (Figure 2), and implies a coefficient of variation of 6 percent. Judging by the coefficient of variation, the model is least accurate in predicting the rate of problematic credit in the financial services sector, and most accurate in the construction sector and in transport and storage.

The LM1 test indicates that in none of the sectors is there any evidence of serial correlation in the residuals, except perhaps in the case of personal credit. The LM2 test includes the lagged residuals for the other sectors in the auxiliary regression. A significant LM2 statistic would imply that the residuals are cross-autocorrelated with residuals in other sectors. None of the LM2 statistics is statistically significant. Because the model residuals are serially independent within and between sectors, the cross-lagged dependent variables used to estimate the coefficients of contagion are weakly exogenous. Also, in none of the sectors does the forecasting test indicate that the model fails to predict the rates of problematic credit, except perhaps in transport and storage.

Since we are uncertain that RPC is stationary, we show ADF statistics for the long-run residuals calculated using Equation (5). These ADF statistics clearly show that the long-run residuals are stationary[12], implying that the risk factors account for the trends in credit risk. Finally, we show the KPSS statistics for the residuals obtained from a full dynamic simulation of the model. This statistic takes into account that the contagion effects are jointly determined. In the absence of formal critical values, they suggest, on the whole, that the full dynamic simulation errors are stationary.

Table 9
Correlation Matrix for **Credit Risk Innovations**

	Manufacturing	Construction	Commerce	Hospitality	Transport-Storage	Financial Services
Construction	0.039					
Commerce	0.347	0.021				
Hospitality	0.208	0.030	0.092			
Transport-Storage	0.174	0.184	0.036	0.187		
Financial Services	-0.053	0.079	-0.181	0.216	0.245	
Households	0.139	-0.165	0.025	-0.043	-0.290	0.020

Notes: Bartlett test of sphericity = 26.9, p-value for zero correlations df = 21 is 0.172.

[12] According to Ericsson and Mackinnon (2002), the critical values are about -3.7.

Finally, Table 9 shows the correlation matrix between the residuals of the sectoral models, i.e. the estimated correlation matrix for u_j in Equation (4). Since the critical value of r at $p = 0.05$ is 0.31 the majority of these correlations are not significantly different from zero. The correlations range between 0.347 and -0.29. Bartlett's sphericity test indicates that the correlations in Table 9 are jointly not significantly different from zero.

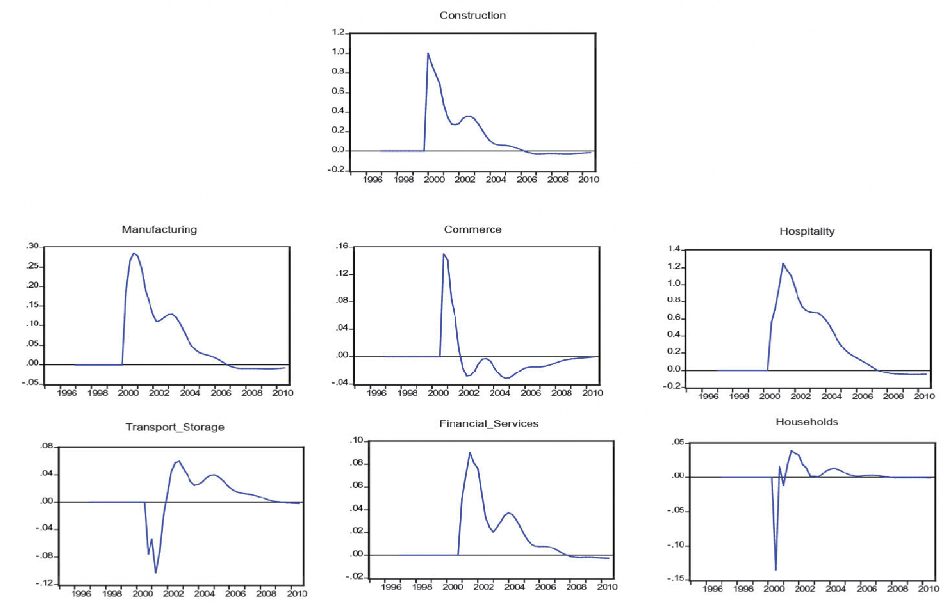
Despite the fact that according to Table 4 the rate of problematic credit is correlated across sectors, the empirical model succeeds in orthogonalizing the residuals. We may consequently rule out correlated innovations as a cause of correlation in credit risk. This result also suggests that contagion does not take place within quarters, since if it did the residuals should be correlated. Jorion and Zhang (2009) report that the contagious effect of counterparty risk on creditors' abnormal equity returns increases and becomes more significant during the 70–day period after the event, which suggests that a quarter might be short enough to capture most if not all of the contagion in bank credit risk. This is an empirical matter, which cannot be determined *a priori*. We show *ex post facto* that sectoral credit risk shocks in the previous quarter (and before) have causal and therefore contagious effects on current credit risk in other sectors.

5. MODEL PROPERTIES: CREDIT RISK PROPAGATION

The empirical model consists of seven dynamic equations, which are related through common factors, correlated factors and contagion. To investigate the properties of the model, we first carry out a full dynamic simulation of the model, which solves for baseline solutions for the state variables (the 7 rates of problematic credit) over the solution period (2000:Q1–2010:Q3). Next, we shock the risk factors to generate new dynamic solutions. The difference between the perturbed and baseline solutions is the impulse response for the relevant shock. Since all shocks are temporary, we expect the impulse responses to die out over time unless the contagion coefficients are unstable.

We begin by simulating the effect of a temporary increase of one percentage point in the rate of problematic credit in the construction sector, which is administered in the first quarter of 2000. The simulated impulse responses are shown in Figure 4. We naturally expect this shock to directly affect the rate of problematic credit in the construction sector, but we are interested in how this shock spills-over to other sectors through contagion. Table 7 shows that credit risk in construction is particularly contagious, affecting credit risk in five other sectors. Therefore, these sectors are directly affected in the simulation. Although credit risk in transport and storage is not directly affected, it is indirectly affected through the directly affected sectors. Furthermore, contagion boomerangs back onto credit risk in construction. Figure 4 shows that credit risk shocks in construction increase credit risk in manufacturing, hospitality, commerce and financial services, and initially decrease credit risk in transport and storage. The largest effect is in the hospitality sector, where it peaks at 1.1, and the smallest is in credit to households. Although most of the propagation occurs within a year of the shock, it takes about three years for the effects of the shock to die out. The impulse responses indicate that the propagation of credit risk is a self-limiting process and that the epidemiology of credit risk is stable. They also show that in some cases, such as commerce, contagion may also induce overshooting.

Figure 4
Impulse Responses for Credit Risk Shock in Construction

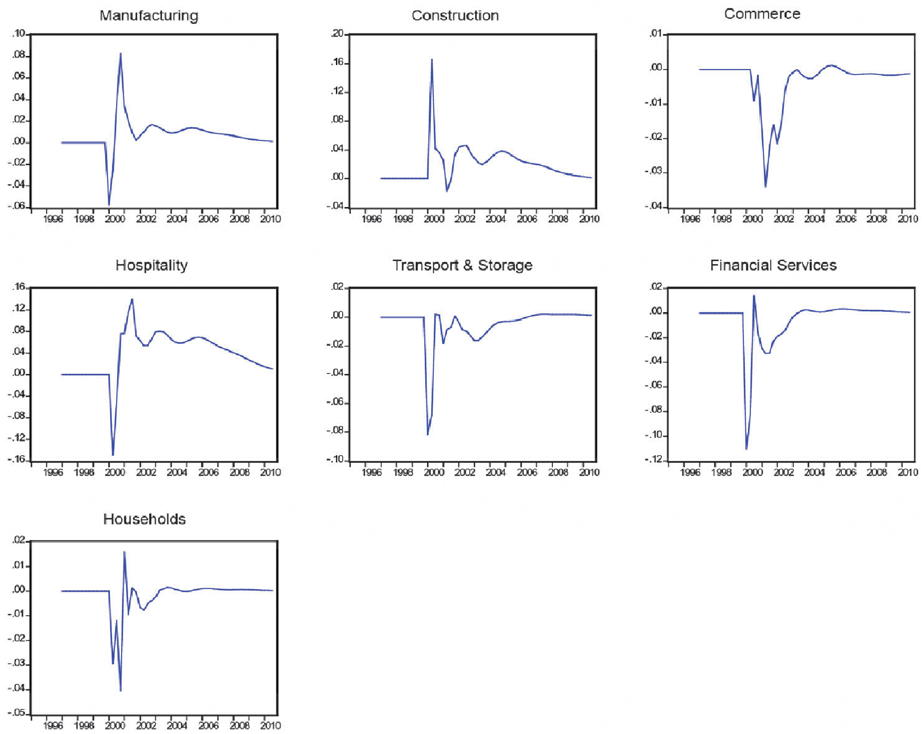


Next, we administer a "cyclical shock", which has a pervasive effect on all sectors. Specifically, we administer a positive but temporary shock of one percentage point in the Bank of Israel's coincident indicator (CI) of economic activity in the first quarter of 2000. Although this indicator does not feature directly in Tables 5 as a risk factor, many specified risk factors are correlated with it. These risk factors are regressed on CI to estimate their procyclical or anticyclical sensitivity.[13] Therefore the shock to CI transmits itself to other macro risk factors, as well as to some of the sectoral risk factors. However, it does not

[13] The following regression was estimated for risk factor h: $z_{ht} = a_h + b_hCI_t + d_hz_{ht-1} + e_hCI_{t-1} + v_{ht}$, where CI denotes the coincident indicator. The macroeconomic risk factors include investment, consumption, the unemployment rate, real wages, exports and the TASE index. Some macroeconomic factors, such as the exchange rate, are acyclical. Some of the sectoral factors, such as turnover (construction, transport and storage), industrial production, employment (financial services), real wages (transport and storage) and internal tourism, are cyclical.

transmit itself to sectoral risk factors such as foreign tourism or the price of diesel fuel. The impulse responses are plotted in Figure 5.

Figure 5
Cyclical Impulse Responses



Because the cyclical shock is positive, credit risk initially falls in all sectors except for construction, where the drivers of credit risk are anti-cyclical. In some sectors, such as commerce, the fall is protracted and monotonic, while in others, such as manufacturing, the fall is short-lived and non-monotonic. Indeed, in manufacturing and hospitality, credit risk increases after about a year and convergence is from above rather than below.

Table 10 shows the contribution of contagion to the correlations for credit risk. The correlations shown in the columns labeled by FDS refer to the correlations from the full dynamic simulation of the model (2000:Q1–2010:Q3) to which reference has already been made. These correlations may be compared with their counterparts in the data shown in Table 4. The FDS and data correlations differ because the former are calculated from base-run solutions, which differ from the data, and because the data correlations refer to the

1997:Q1–2010:Q3 period. Nevertheless, the two sets of correlations are broadly similar (except for the correlation between households and commerce).

Next, we carry out a full dynamic simulation of the model with the contagion coefficients shown in Table 7 set to zero. This simulation produces counterfactual data for what would have happened to credit risk in the absence of contagion. In Table 10 we use CF to denote the credit risk correlations from these counterfactual data. The differences between the FDS and CF correlations estimate the contribution of contagion to correlation.

Table 10
Contribution of Contagion to Correlation

	Construction		Commerce		Hospitality		Transport & Services		Financial Services		Households	
	FDS	**CF**	**FDS**	**CF**	**FDS**	**CF**	**FDS**	**CF**	**FDS**	**CF**	**FDS**	**CF**
Manufacturing	0.17	0.03	0.74	0.58	0.01	-0.57	0.18	0.16	0.11	0.13	0.46	0.72
Construction			-0.03	-0.38	0.78	0.27	0.30	0.66	0.63	0.54	-0.58	-0.64
Commerce					0.10	-0.01	-0.19	-0.28	0.11	0.23	-0.46	-0.38
Hospitality							-0.10	-0.06	0.69	0.49	-0.46	-0.38
Transport & Storage									0.20	0.33	-0.28	-0.32
Financial Services											-0.33	0.03

Notes: FDS: correlations from base-run solutions. CF: correlations from counterfactual simulations with contagion coefficients set to zero.

For example, the credit risk correlation between manufacturing and construction would have been 0.03 in the absence of contagion, rather than 0.17. Table 10 includes cases such as manufacturing-construction, in which the correlation is less positive. It also includes cases in which it is less negative, such as households-hospitality. There are cases where the absolute correlations increase (e.g. manufacturing-households), and there are even cases where correlations change sign. It might have been surmised that contagion must increase correlation absolutely. This would have been true if the coefficients of correlation were all positive, in which case contagion would have made credit risk more correlated, or if all the contagion coefficients were negative, in which case contagion would have made credit risk less correlated. However, because the contagion coefficients in Table 7 are of mixed signs, it is not clear how contagion should affect these correlations. Out of the 21 correlations in Table 10, there are 11 correlations that decrease in absolute size. Therefore, in the present case, the average effect of contagion on correlation is close to zero.

Finally, we decompose credit risk volatility as measured by the standard deviation of credit risk into three components, macroeconomic (m), sectoral (s) and idiosyncratic (u). We illustrate using a simplified model in which credit risk is autoregressive but m, s and u are not:

(6) $$y_t = \lambda y_{t-1} + m_t + s_t + u_t$$

The unconditional variance of y according to Equation (6) is:

(7) $$\mathrm{var}(y) = \frac{\mathrm{var}(m) + \mathrm{var}(s) + \mathrm{var}(u) + 2\mathrm{cov}(ms) + 2\lambda[\mathrm{cov}(m_t y_{t-1}) + \mathrm{cov}(s_t y_{t-1})]}{1-\lambda^2}$$

Equation (7) uses the fact that by definition cov(um) = cov(us) = cov(uy_{-1}) = 0.

To calculate the idiosyncratic component, var(u), we perturb the base-run for 2000–2010 by using the estimated residuals of the credit risk model (which are assumed to be zero in the base-run). The standard deviation of the difference between the base-run and the simulation measures the contribution to the volatility in credit risk induced by idiosyncratic risk shocks (Row 1 in Table 11). This simulation takes account of the dynamic effects of these shocks as they propagate through inertia within sectors and contagion between them. The contribution is largest in the hospitality sector and smallest among households.

Row 2 in Table 11 shows the contributions of the macroeconomic risk factors to the volatility in credit risk. They are calculated by running a counterfactual simulation in which all the macroeconomic risk factors are held constant at their level in the first quarter of 2000. The standard deviation of the difference between the base-run and the perturbation is shown in Row 2. The contribution of macroeconomic risk factors to the volatility in credit risk is also largest in hospitality and smallest among households.

The same applies to the contributions of sectoral risk factors to credit risk volatility, which are shown in Row 3 of Table 11. They are calculated by running a counterfactual simulation in which all the sectoral risk factors are frozen at their level in the first quarter of 2000. The standard deviation of the difference between the base-run and the perturbation is shown in Row 2.

We also carried out a counterfactual simulation in which the Bank of Israel's business cycle CI is held fixed from 2000:Q1, and in which the cyclical macroeconomic and sectoral risk factors are dynamically correlated to CI. The difference between credit risk in the base-run and in the counterfactual simulation measures the contribution of the business cycle to credit risk. Row 4 in Table 11 shows the contribution of the business cycle to the volatility in credit risk. Once again, this contribution is largest in the hospitality sector and smallest among households.

Row 5 of Table 11 records standard deviations of the sectoral rates of problematic credit during the 2000–2010 period. The column sums of the components in Rows 1–3 do not equal the total in Row 5 for several reasons. First, the standard deviation of a sum does not equal the sum of the component standard deviations. Second, the counterfactual simulations are carried out separately rather than jointly. Nevertheless, the decomposition in Table 11 sheds light on the relative contributions of the different sources of risk to the volatility of credit risk within sectors. For example, in the manufacturing sector the major component of credit risk is sectoral, in the household sector the major component is macroeconomic, and in the hospitality sector the largest component is idiosyncratic. The cyclical and macroeconomic components are strongest in the hospitality sector in absolute terms, but in relative terms are strongest in the household sector. The most volatile sector is hospitality and the least volatile is the household sector.

Table 11
Decomposing the Standard Deviation of Bank Credit Risk: 2000–2010

	Manufacturing	Construction	Commerce	Hospitality	Transport and Storage	Financial Services	Households
1 Idiosyncratic	1.73	6.53	0.33	15.31	3.60	0.44	0.23
2 Macroeconomic	0.99	2.92	0.76	4.67	1.53	1.47	0.69
3 Sectoral	3.73	6.55	0.50	13.65	3.98	0.35	0.24
4 Cyclical	0.78	2.50	1.09	4.76	1.04	1.45	0.38
5 Credit risk	2.11	3.39	1.44	9.25	7.01	1.66	0.83

6. SUMMARY AND CONCLUSIONS

We have proposed a methodology for analyzing bank credit risk, which distinguishes between contagion and correlation on the one hand, and risk factors that are macroeconomic, sectoral and idiosyncratic on the other. An empirical illustration was presented, using data published by the Bank of Israel, in which credit risk propagates within and between economic sectors. This methodology differs from conventional methods for analyzing bank credit risk, in which the units of observation consist of individual creditors rather than sectors. We see our methodology as a complement rather than a substitute for creditor-based methods. The latter are naturally superior in exploiting micro-information on individual credit risk. However, they are less able to identify systemic risk, which expresses itself in contagion and correlation in the propagation of bank credit risk. Systemic risk is like the forest, which is more difficult to detect among individual creditors (the trees). Ideally, stress-testing should be informed by both types of methods. Our methodology may be applied to the banking system as a whole, or it may be applied by individual banks using their proprietary data on credit risk by economic sector. Indeed, in some countries such as Italy these data are public.

Contagion is malignant and infectious if credit risk in one sector increases credit risk elsewhere. However, contagion is benign and immunizing when credit risk in one sector reduces credit risk elsewhere. The propagation of credit risk is intensified by malignant contagion and mitigated by benign contagion. The construction sector is particularly infectious; bank credit risk in construction increases credit risk in most sectors, which intensifies the propagation of credit risk. On the other hand, credit risk elsewhere reduces credit risk in the construction sector through benign contagion, which mitigates the propagation of credit risk. Credit risk in the transport and storage sector is benignly contagious. Some sectors, such as hospitality, are not contagious at all, but credit risk in them is highly volatile. The household sector is the most stable sector, but it is malignantly contagious.

Contagion significantly increases the volatility of bank credit risk regardless of whether it is malignant or benign. On the other hand, contagion in Israel does not greatly increase the correlation in bank credit risk because benign contagion mitigates the effect of malignant contagion. In general, we suggest that banking supervision authorities should distinguish between the effect of contagion on volatility, which is always positive, and the effect of contagion on correlation, which is positive if the dominant form of contagion is malignant.

Israel has been fortunate in having a stable banking system at a time when banking systems in a number of OECD countries have undergone severe strain. Rates of problematic credit declined during the reviewed period (1997–2010) and have continued to decline subsequently. In terms of our model, these developments are a result of the relative and absolute macroeconomic stability in Israel. More recently, arrangements have been implemented regarding bank equity and liquidity ratios, which are stricter than those recommended in Basel III. In addition, larger banks have stricter ratios than smaller banks.

Israel's banking system was stable despite the absence of financial instruments such as swaps and contingent convertibles that enable banks to securitize problematic credit. Such financial instruments were issued in Israel for the first time in 2015, and their further development will enable Israel's banking system to cope with credit risk crises should they arise.

The Supervisor of Banks (Annual Survey 2015) sees mortgages as the main potential threat to bank stability. Mortgages and housing finance increased as a share of bank lending, from 16 percent in 2001 to 32 percent in 2015. This happened for several reasons. First, especially during the last decade, the mortgage market has developed and matured institutionally. Second, home prices have increased by 100 percent in real terms since 2007 so that larger mortgages are required. Third, demographic growth has increased the demand for housing. Fourth, as living standards improve, home sizes have increased. Fifth, as a result of the Bank of Israel's "zero" interest rate policy, mortgages became cheap. For all of these reasons housing finance as a share of bank credit has grown sharply.

The Supervisor of Banks has tried to restrain the growth of mortgages by requiring greater equity in housing finance. The fear is that if monetary policy is normalized, and housing finance becomes more expensive, mortgage borrowers will be unable to cover their mortgage payments at a time when home prices are falling. According to our results, bank credit risk among households was not affected by the 25-percent fall in real home prices between 2000 and 2006, or by changes in the cost of housing finance. What is of much greater importance than mortgages is credit risk in construction. According to our results there are two aspects to this. First, construction is greatly over-represented in bank credit risk. Second, credit risk in construction is highly contagious relative to other sectors. By contrast, our results suggest that the growth in mortgages is unlikely to be a major problem if monetary policy is normalized. In any case, credit risk among households is less contagious than in the construction sector.

Finally, as mentioned in Section 2.2, insurance-induced contagion is welfare improving. This paper does not discuss whether there is too much contagion or too little. Instead, our concern has been with measuring contagion. If there is too much contagion policy makers should try to reduce it. If there is too little contagion they should try to increase it, possibly by encouraging insurance. However, such policies lie beyond the present terms of reference.

Appendix

a. A Two-Sector Toy Model

Apart from fixed effects there are two symmetric sectors (A and B) and one macroeconomic factor (z). Credit risk shocks have the same variance (σ^2) in both sectors and their correlation coefficient is denoted by ρ. Equation (1) in the text therefore becomes:

$$y_{At} = \alpha_A + \theta y_{Bt-1} + \lambda y_{At-1} + \phi z_t + u_{At} \qquad (A1)$$

$$y_{Bt} = \alpha_B + \theta y_{At-1} + \lambda y_{Bt-1} + \phi z_t + u_{Bt} \qquad (A2)$$

The variances and covariance[14] for credit risk may be expressed in matrix form:

$$(A.3) \quad \begin{bmatrix} 1-\lambda^2 L & -\theta^2 L & -2\theta\lambda L \\ -\theta^2 L & 1-\lambda^2 L & -2\theta\lambda L \\ -\theta\lambda L & -\theta\lambda L & 1-(\theta^2+\lambda^2)L \end{bmatrix} \begin{bmatrix} \mathrm{var}(Y_{At}) \\ \mathrm{var}(Y_{Bt}) \\ \mathrm{cov}(Y_{At}Y_{Bt}) \end{bmatrix} = \begin{bmatrix} \phi^2\sigma_z^2 + \sigma^2 \\ \phi^2\sigma_z^2 + \sigma^2 \\ \phi^2\sigma_z^2 + \rho\sigma^2 \end{bmatrix}$$

where L denotes the lag operator. The determinant of the coefficient matrix in Equation (A3) is:

$$d = 1 + \pi_1 L + \pi_2 L^2 + \pi_3 L^3$$

$$\pi_1 = -(3\lambda^2 + \theta^2) \qquad \pi_2 = 3\lambda^4 - \theta^4 + 2\lambda^2\theta^2 \qquad \pi_3 = (\theta^2 - \lambda^2)^2$$

Solving Equation (A3) for the conditional covariance of credit risk, we obtain:

$$\mathrm{cov}(y_{At}y_{Bt}) = \sum_{i=1}^{3} \pi_i \,\mathrm{cov}(y_{At-i}y_{Bt-i}) + \pi_4\sigma^2 + \pi_5\phi^2\sigma_z^2 + \sum_{a=1}^{3} A_a r_a^t \qquad (A4)$$

$$\pi_4 = \rho(1-\lambda^2)^2 + \theta\lambda - \rho\theta^4 + 2\lambda\theta^3 + \theta\lambda(1-\lambda^2)$$

$$\pi_5 = (1-\lambda^2)^2 + 2\theta\lambda(1-\lambda^2) - \theta^4 + 2\lambda\theta^3$$

where r_a denotes the three eigenvalues of the coefficient matrix in Equation (A3) and A_a the associated arbitrary constants. The conditional covariance of credit risk is a third order autoregressive process, which converges to its unconditional counterpart:

$$\mathrm{cov}(y_A y_B) = \frac{\pi_4\sigma^2 + \pi_5\phi^2\sigma_z^2}{1 + \pi_1 + \pi_2 + \pi_3} \qquad (A5)$$

[14] The variances are calculated directly from equations (5A) and (5B). The covariance is obtained by multiplying equations (5A) and (5B).

Solving Equation (A3) for the unconditional variance of credit risk in sectors A and B we obtain:

$$\mathrm{var}(y_t) = \sum_{i=1}^{3} \pi_i \,\mathrm{var}(y_{t-1}) + \pi_6\sigma^2 + \pi_7\phi^2\sigma_z^2 + \sum_{a=1}^{3} B_a r_a^t \qquad (A6)$$

$$\pi_6 = 1 - 2\lambda^2 + (1+2\theta^2)\lambda^4 - \theta^4 + 2\rho\theta\lambda(1-\lambda^2)$$

$$\pi_7 = 1 - 2\lambda^2 + (1+2\theta^2)\lambda^4 - \theta^4 + 2\theta\lambda(1+\theta^2-\lambda^2)$$

where B_a denotes the arbitrary constants. The conditional variance of credit risk is also a third order autoregressive process, which converges to:

$$\mathrm{var}(y) = \frac{\pi_6\sigma^2 + \pi_7\phi^2\sigma_z^2}{1+\pi_1+\pi_2+\pi_3} \qquad (A7)$$

$$1+\pi_1+\pi_2+\pi_3 = 1-\theta^2[1+\theta^2-\theta^4+\theta^2\lambda^2+2(\theta\lambda+1-\lambda^3)] - \lambda^2(3+\lambda^2-\lambda^4+2\lambda)$$

Finally, dividing Equation (A5) by Equation (A7) gives the unconditional correlation of credit risk between the two sectors:

$$r = \frac{\pi_4\sigma^2 + \pi_5\phi^2\sigma_z^2}{\pi_6\sigma^2 + \pi_7\phi^2\sigma_z^2} \qquad (A8)$$

Equation (A8) shows that the correlation in credit risk depends on the structural parameters θ, ϕ, λ, ρ, σ, and σ_z.

The correlation may be negative if contagion is benign ($\theta < 0$) rather than malignant ($\theta > 0$).[15] If $\phi = \rho = 0$ the correlation simplifies to π_4/π_6. Since π_4 depends on θ and θ^3, and π_6 depends on θ^2 and θ^4, benign contagion induces negative correlation. Benign contagion also reduces volatility since the numerator in Equation (10) decreases with π_6 and π_7, while the denominator does not depend on the sign of θ.

Benign contagion also arises in epidemiological models. Exposure of a susceptible to an infective may induce immunity instead of infection. In our context, benign contagion arises when B's credit risk is to A's advantage, for example because B is a rival or a competitor to A (Jorion and Zhang, 2007), or because banks lend less to sector B and more to sector A. However, if A's business depends on B contagion will be malignant or "bad" in the sense of Jorion and Zhang.

[15] Jorion and Zhang (2007) refer to $\theta < 0$ as "good contagion" in terms of a "competition effect", rather than benign contagion. However, the difference is largely semantic.

b. Instantaneous Contagion

In Equations (A1) and (A2), it is assumed that contagion takes one period. If contagion also takes place during period t Equations (A1) and (A2) continue to identify contagion but its interpretation is affected. To show this we modify them by specifying contemporaneous contagious effects (ψ):

$$y_{At} = \alpha_A + \psi y_{Bt} + \theta y_{Bt-1} + \lambda y_{At-1} + \phi z_t + u_{At} \qquad (A9)$$
$$y_{Bt} = \alpha_B + \psi y_{At} + \theta y_{At-1} + \lambda y_{Bt-1} + \phi z_t + u_{Bt} \qquad (A10)$$

The VAR model generated by Equations (A9) and (A10) is:

$$y_{At} = \pi_A + \kappa y_{Bt-1} + \rho y_{At-1} + \eta z_t + w_{At} \qquad (A11)$$
$$y_{Bt} = \pi_B + \kappa y_{At-1} + \rho y_{Bt-1} + \eta z_t + w_{Bt} \qquad (A12)$$
$$\pi_A = \frac{\alpha_A + \psi\alpha_B}{1-\psi^2},\ \kappa = \frac{\theta+\psi\lambda}{1-\psi^2},\ \rho = \frac{\lambda+\psi\theta}{1-\psi^2}, \eta = \phi\frac{1+\psi}{1-\psi^2}, w_{At} = \frac{u_{At}+\psi u_{Bt}}{1-\psi^2}$$
$$\pi_B = \frac{\alpha_B + \psi\alpha_A}{1-\psi^2}, w_{Bt} = \frac{u_{Bt}+\psi u_{At}}{1-\psi^2}$$

Equations (A11) and (A12) have the same first-order structure as Equations (A1) and (A2), but their coefficients have a different interpretation. The contagion coefficient κ estimates the joint effects of intra-temporal (ψ) and inter-temporal (θ) contagion. If there is no contagion, κ = 0. If contagion is entirely intra-temporal (θ = 0), κ identifies ψ. Also, whereas u_A and u_B may be independent, w_A and w_B are dependent. Unfortunately, ψ and θ are not identified because there is an identification deficit of 1.[16] In SVAR models the identification deficit is closed by making untestable identifying assumptions, but we refrain from this. The important point is that even if contagion was intra-temporal, our methodology would detect it. In addition, if the VAR residuals are independent, it suggests that ψ = 0 provided the structural residuals (u_A and u_B) are independent.

[16] There would be 12 unknown structural parameters to be estimated if the model is not symmetrical, comprising an intercept, four slope parameters and σ_u for each of Equations (13) and (14). The VAR model comprises only 11 parameters comprising an intercept, three slope parameters and σ_w for each of Equations (15) and (16), and σ_{wAwB}.

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