



The procyclicality of Basel III leverage: Elasticity-based indicators and the Kalman filter†

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Abstract

Even though off-balance sheet (OBS) activities greatly contribute to bank risk, most financial indicators are essentially based on on-balance-sheet data. Basel III intends to correct this situation with a leverage requirement ratio incorporating some OBS components. However, the rather unique Canadian experience with a similar mandatory indicator suggests that a broader leverage measure only partly alleviates the problem. In particular, a mandatory leverage of this kind tends to overemphasize ex post deleveraging. In this paper, we introduce a dynamic setting based on a Kalman filter procedure to study a number of elasticity-based indicators encompassing embedded and economic leverages. This new methodology enables the detection of the build-up in systemic risk years before what the traditional assets to equity ratio measure predicts. In this respect, most elasticity measures of leverage appear in line with the historical episodes, well tracking the cyclical pattern of bank leverage. More importantly, these time-varying indicators suggest that OBS banking exerts a stronger influence on bank risk during expansion periods.

Keywords: Leverage, Banking, Off-balance sheet activities, Liquidity, Basel III, Kalman Filter.
JEL classification: C13, C22, C51, G21, G32.

La procyclicité du levier proposé par Bâle III : Indicateurs fondés sur les élasticités et le filtre de Kalman

Résumé

Même si les activités hors bilan (OBS) contribuent grandement au risque bancaire, la plupart des indicateurs financiers sont basés essentiellement sur des données de bilan. Le comité de Bâle III entend corriger cette situation en proposant un levier qui incorpore certaines composantes hors bilan. Cependant, l'expérience particulière du Canada avec un indicateur similaire suggère qu'une mesure plus englobante de levier ne fait qu'atténuer le problème. En particulier, une telle mesure tend à accentuer le désendettement ex post. Dans ce papier, nous introduisons un cadre dynamique basé sur la procédure du filtre de Kalman, de manière à étudier quelques indicateurs basés sur le concept d'élasticité qui intègrent les leviers implicites et économiques. Cette nouvelle méthodologie nous permet de détecter la progression du risque systémique plusieurs années avant l'indicateur classique du ratio actifs sur équité. À cet égard, la plupart de nos mesures de levier semblent au diapason des épisodes historiques, c'est-à-dire qu'elles rendent compte de manière satisfaisante des cycles du levier bancaire. Fait important, ces indicateurs, variables dans le temps, suggèrent que les activités bancaires hors bilan exercent une influence plus marquée sur le risque systémique durant les périodes de haute conjoncture.

Mots-clefs : Levier, banque, activités hors bilan, liquidité, Bâle III, filtre de Kalman.
Classification JEL : C13, C22, C51, G21, G32.

1. Introduction

Since banks were allowed to conduct new types of off-balance-sheet activities (e.g. non-traditional activities such as underwriting and securitization) their financial results have become more volatile. This increase in earnings fluctuations is generally attributed to the volatility of OBS activities (Stiroh 2004, 2006a, 2006b; Stiroh and Rumble 2006; Calmès and Liu 2009; Calmès and Théoret 2009, 2010). For example, following the emergence of market-oriented banking (i.e., “shadow banking”, Shin 2009), the fluctuations in Canadian banks net operating income growth have increased *pari passu* with the growing volatility of noninterest income (Figure 1). This volatility trend relates to bank market-oriented business lines, in particular the trading and capital markets activities generating trading and fee income, two extremely volatile noninterest income categories¹ (Figure 2). There is also evidence that the higher risk-taking associated with shadow banking results in greater levels of bank leverage (DeYoung and Roland 2001, Shin 2009, Adrian and Shin 2010).

Insert Figures 1 and 2 here

Leverage is a key financial indicator of bank risk (Hamada 1972, Rhee 1986, Griffin and Dungan 2003, Lorenzoni 2007, Cihak and Schaeck, 2007, Stein 2010). Surprisingly though, despite the cyclical contribution of OBS activities to systemic risk, broad leverage remains an under-researched field in banking. The leverage requirement ratio to be implemented under Basel III incorporates some OBS components, and judging by the Canadian experience with a similar indicator, it should better account for the cy-

¹ Trading income is volatile because it comoves with the stock market. Fee income is volatile because the demand for the products generating such income is strongly conditioned by the phase of the business cycle. For example, credit commitments surge during expansion periods and recede during recessions.

clicality of bank leverage. Nevertheless, this kind of indicator is still mainly based on balance sheet data. As a matter of fact, we argue in this paper that the current leverage formula misses some important dynamic properties of bank risk. In particular, we show that it tends to overemphasize ex post deleveraging.

To our knowledge, DeYoung and Roland (2001) are the first to analyze the bank average degree of total leverage, i.e., an elasticity-based measure of leverage including *all* banking activities. The authors find that market-oriented activities indeed contribute to bank leverage. In our study, we revisit this kind of time-varying indicators with the same motivation. However, compared to DeYoung and Roland (2001), Shin (2009) and Adrian and Shin (2010), our main objective is to examine the dynamics of broad leverage in a set-up specifically designed to rigorously account for the cyclical nature of bank risk. In particular, we propose a new approach based on the Kalman filter to account for the procyclicality of bank leverage recently discussed in Shin (2009). As the dual of a dynamic programming problem, the Kalman filter enables the computation of optimal leverage paths conditional on all the information available at the time of computation (Ljungqvist and Sargent 2004). Our methodology is intended to address one of the major issues associated with elasticity-based measures of leverage, namely their lack of stability. Thanks to the Kalman filter we can generate smoothed time series for any time-varying leverage measure considered.

The main contribution of this paper is to show that OBS activities exert a stronger influence on aggregate leverage during expansion periods, thereby accentuating bank risk procyclicality. We also find that the ratio of liquidity is an important driver of the Kalman-filtered series of leverage. In the context of shadow banking, liquidity is obviously a

significant factor influencing leverage since market-oriented activities provide a *sui generis* source of funding to financial institutions (e.g., Gorton and Pennachi 1990, Loutskina 2010, Stein 2011). Adding to this literature, we find that the sensitivity of bank leverage to liquidity is strongly conditioned by the phase of the business cycle. Our results suggest that OBS-generated liquidity decreases on-balance-sheet liquidity during expansion, and accentuates the deleveraging process in contraction periods. In other words, broad liquidity compounds the procyclical impact of OBS banking on systemic risk.

This paper is organized as follows. Section 2 discusses some drawbacks of the traditional approach to bank leverage. Section 3 describes our elasticity-based measures and the Kalman filter methodology we employ to derive optimal leverage indicators. In section 4, we present the data and some basic empirical facts, while in the fifth section we analyze the cyclical pattern of our leverage indicators before concluding in the last section.

Insert Figure 3 here

2. Beyond the traditional approach to leverage measurement

The leverage measures usually monitored by regulatory agencies are defined in terms of accounting ratios computed directly with balance sheet data, the most usual one being the ratio of assets to equity. Given its resemblance with the Basel III regulatory leverage, an interesting extension of the traditional ratio is the mandatory measure of leverage imposed by the Canadian Office of the Superintendent of Financial Institutions (OSFI)² since 1982. Indeed, this mandatory measure is broader than the simple ratio of assets to equity since it adds to assets the loan commitments, and to equity the long-term

² The OSFI supervises the Canadian microprudential policy.

debentures. Figure 3 helps compare the behaviour of these two standard measures of leverage since the 1996 amendment to Basel I and the inception of the VaR (Value-at-Risk). In general, the traditional measure of leverage is relatively stable, at least before the sub-prime crisis (Figure 3). By contrast, the mandatory leverage ratio rises as banks expand their loan commitments (Figure 4). Hence, compared to the traditional assets to equity ratio, the trend of the mandatory leverage appears more cyclical, increasing during expansion periods and contracting in recessions. In this sense, it seems better fitted for macroprudential analysis. Importantly however, note that the fluctuations of this indicator appear qualitatively moderate considering the substantial increase in bank earnings volatility observed during the period. Intuitively, the reason why it should be the case relates to the fact that this type of leverage indicator still excludes highly volatile OBS items such as trading and capital markets activities.

Insert Figure 4 here

To corroborate this view, it is instructive to analyze the cyclicity of the standard leverage measures with respect to bank assets, by relating asset growth to leverage growth with a scatter diagram in the spirit of Shin (2009). Consistent with the literature, Figure 5 confirms the positive relationship between asset growth and traditional leverage growth. Over the 1997-2009 period, the correlation between these two variables is equal to 0.31 and significant at the 95% confidence level. There is thus some “procyclicality” in the behaviour of the traditional leverage ratio. However, on this dimension, the scatter diagram relating the growth of the mandatory leverage to asset growth displays weak procyclicality, or even countercyclicality (Figure 5). One plausible explanation for this drawback is that the OBS items currently included in this type of leverage indicator are

little correlated with assets. For example, loan commitments are indeed related to assets, but with a lag, thus imparting a rich dynamic structure to bank risk, with the unintended consequence of partly dampening the sensitivity of the indicator to asset changes. In other words, despite its merits, the mandatory leverage seems to understate an essential dimension of bank risk, namely the procyclicality of leverage.

Insert Figure 5 here

Another motivation to look beyond the traditional approach to leverage measurement is that, with the apparition of OBS activities, the mere notion of liquidity has drastically changed. Consider for example the behaviour of the bank ratio of liquidity, as defined by the ratio of liquidity (cash, short-term paper and government bonds) to assets (Figure 6). This ratio peaks at 21% in 1996, and decreases progressively to 11% in the middle of 2007³, precisely during the period when shadow banking develops (Calmès and Théoret 2010, 2011). Since off-balance-sheet assets (e.g., securitized assets) can provide new forms of liquidity, banks need less on-balance-sheet liquidity to cover their risk. Indeed, market-oriented activities generate liquidity of their own, limiting the need for conventional sources of liquidities (Gorton and Pennacchi 1990, Loutskina 2009, Stein 2010, Lucas and Stokey 2011). As banks expand their non-traditional activities, they can lower the stock of their on-balance-sheet liquidity to optimally balance liquidity on and off-balance-sheet (Jones 2000, Calomiris and Mason 2004, Ambrose et al. 2005, Kling 2009, Brunermeier 2010, Cardone et al. 2010). Obviously, this change in the nature of liquidity must have an impact on bank leverage. Intuitively, since market-oriented activities exert an influence on liquidity, the latter should also affect the cyclical behaviour of bank lev-

³ Note that the sharp increase in the bank liquidity ratio observed from 1990 to 1993 is mainly due to the severe economic slowdown which prevailed during this period.

erage. As evidence of this, if we build a leverage measure considering balance sheet liquidity as banks' negative debt⁴, expressing leverage as $\left[\frac{\text{debt} - \text{liquidity}}{\text{assets}} \right]$, net leverage effectively tracks the build-up in systemic risk observed before the 2007 crisis (Figure 7). Actual leverage increases even if this does not show up in the traditional assets to equity ratio measure.

[Insert Figures 6 and 7 here]

In summary, the traditional measure of bank leverage based on balance sheet variables, the assets to equity ratio, seems to be an incomplete measure of bank risk because it tends to be strongly mean-reverting, banks targeting a leverage level preventing the indicator to properly detect banks' actual risk management. In this respect, extensions like the Canadian mandatory leverage perform better as they partly include variables related to broad liquidity and OBS activities. However, considering the OBS components currently included in the Basel III leverage ratio requirement and the Canadian mandatory leverage, this kind of indicators might not be as procyclical as broader measures could suggest. To properly investigate this question, we need to analyze the cyclical properties of various leverage indicators with a full-blown framework, as discussed below.

3. The construction of the elasticity-based indicators

A technical reason why the standard leverage measures could be inadequate to monitor bank risk is that they are fairly time-invariant. Compared to accounting ratios, elastic-

⁴ As argued by Kashyap and Stein (1993, p.19): "Selling Treasury bills and issuing certificates of deposits are closely related strategies". Indeed, reducing liquidities or increasing leverage are very close strategies. For example, Adrian and Shin (2011) state that the demand for collateral assets actually increases leverage.

ity-based measures of bank leverage seem *a priori* more suited to measure the sensitivity of a key proxy of bank performance, Y (e.g., equity or earnings), to a “support”, X (e.g., assets or net operating income), because unlike the standard ratios, the degree of leverage is free from questionable assumptions (except, maybe, for the implicit assumption of linearity). In particular, it is no longer necessary to assume that the variations in equity capture all the changes in asset values, as it is the case with both the Canadian mandatory leverage and the Basel III leverage ratio requirement.

3.1. The elasticity-based leverage measures

If the variable X has a leveraging effect on the variable Y , we measure the sensitivity of Y to variations in X with the elasticity of Y with respect to X . In practice however, bank leverage is often defined as the assets to equity ratio because variations in assets and equity are assumed to cancel out in the long-run. Since, by accounting identity, assets are the sum of debt and equity, this ratio is also equal to $\frac{debt}{equity} + 1$, or to simplify, proportional to $\frac{debt}{equity}$. In other words, in the standard measures, the value of equity is assumed to capture all gains and losses on asset positions, and equity is then considered *de facto* as a residual. However, in the context of market-oriented banking, capital losses can be funded by additional debt or by asset sales without directly influencing equity. Therefore, with OBS banking, the relationship between the changes in assets and the changes in equity is no longer a one-for-one mapping. In this environment, to cast bank leverage in a financial stability framework, it is actually preferable to depart from the traditional approach and consider time-varying measures of leverage. As a matter of fact,

macroprudential policy is primarily concerned by the short-term fluctuations in bank risk, and elasticity-based indicators are thus the relevant leverage measures to monitor banking stability.

Following DeYoung and Roland 2001, in this paper we analyze the degree of total leverage (*DTL*), one of the most studied indicators in the banking literature. One attractive feature of this elasticity-based measure is that it includes all banking activities, and in particular every component of OBS activities, and not just loan commitments – as in the case of the Basel III-type of leverage indicators such as the Canadian mandatory leverage. As benchmark measures, in addition to *DTL*, we also consider the elasticity version of the assets to equity ratio and of the mandatory leverage. Methodologically, this benchmarking helps illustrate the extent to which the drawbacks of the standard measures can be addressed with their associated time-varying counterparts.

3.2 Kalman filtering and optimal leverage

Before examining the cyclical properties of bank leverage, we first need to smooth out the time-varying leverage series in order to work with optimal levels instead of noisy variables. To achieve this goal, we apply the Kalman filter to our elasticity constructs. Thanks to this methodology, we can model the regressors coefficient dynamics – the time-varying parameters – and simulate leverage optimal trajectories over the whole sample.

To compute the elasticity of Y with respect to X , authors generally assume that:

$$Y = AX^\beta \quad (1)$$

where β is the elasticity. Taking the logarithms on both sides of (1), we obtain:

$$\log(Y) = \log(A) + \beta \log(X) \quad (2)$$

and taking derivatives, we have:

$$\beta = \frac{d \log(Y)}{d \log(X)} = \frac{dY}{dX} \frac{X}{Y} \quad (3)$$

which corresponds to the elasticity definition of leverage. To implement the Kalman filter we then rely on equation (2). Assume the following leverage model, composed of a measure or observation equation⁵:

$$\log(\pi_t) = \varphi_1 + lev_t \log(OR_t) + \varepsilon_t \quad (4)$$

lev being leverage, and a transition or state equation:

$$lev_{t+1} = \varphi_2 + \varphi_3 lev_t + \eta_t \quad (5)$$

where π_t stands for earnings, OR_t is the operating revenue; φ_i are the parameters we estimate; ε_t is a Gaussian noise with variance v_{1t} , and η_t is a Gaussian noise with variance v_{2t} . In this model, lev_t is the state or unobserved variable we want to estimate. The resulting simulated state series is our proxy for lev over the sample period. At time $t-1$, we compute the estimates of lev_{t-1} , of its variance, ω_{t-1} , and of the coefficients $\varphi_{i,t-1}$. For instance, at $t=0$, we need preliminary estimates (seed values) for lev_0 and ω_0 . Since these values are unknown, we assume that $lev_0 = 0$, and that ω_0 is high enough to account for the uncertainty related to the preliminary estimation of lev . Then the three steps of the simulation are the following.

Step 1 is the forecast step. The filter computes two forecasts: (i) $lev_{t|t-1}$, the forecast of lev_t a time $t-1$, which is the conditional expectation of lev_t given the information

⁵ For the sake of simplicity, we do not expose here the series detrending, a prerequisite to Kalman filtering. Detrending is detailed in the empirical section.

available at time $t-1$; and (ii) $\omega_{t|t-1}$, the forecast of ω_t at time $t-1$, which is the conditional expectation of ω_t at time $t-1$. These forecasts are unbiased conditional expectations computed as:

$$lev_{t|t-1} = \varphi_{2,t-1} + \varphi_{3,t-1} lev_{t-1} \quad (6)$$

$$\omega_{t|t-1} = \varphi_{3,t-1}^2 \omega_{t-1} + v_{2,t-1} \quad (7)$$

Step 2 is a revision step. At time t , new information on π_t is available. We can thus compute the forecast error v_t :

$$v_t = \log(\pi_t) - \varphi_{1,t-1} - lev_{t-1} \log(OR_{t-1}) \quad (8)$$

The variance of v_t , represented by ψ_t , is thus:

$$\psi_t = [\log(OR_{t-1})]^2 \omega_{t|t-1} + v_{1,t-1} \quad (9)$$

We then use v_t and ψ_t to revise lev_t and its variance ω_t :

$$lev_t = lev_{t|t-1} + \frac{\log(OR_{t-1}) \times \omega_{t|t-1} \times v_t}{\psi_t} \quad (10)$$

$$\omega_t = \omega_{t|t-1} + \frac{[\log(OR_{t-1})]^2 \times \omega_{t|t-1}^2}{\psi_t} \quad (11)$$

The two last estimators are the conditionally unbiased estimators which minimize the variances. Kalman filter is thus *optimal* in the sense that it is the best estimator within the class of linear estimators.

Finally, step 3 is the parameter estimation step. We resort to the maximum likelihood estimation method to estimate the parameters φ_i , the maximum likelihood function being:

$$\ell = -\frac{1}{2} \sum_t \log(\psi_t) - \frac{1}{2} \sum_t \frac{v_t^2}{\psi_t} \quad (12)$$

We next move to time $t+1$ and repeat the three steps until the end of the sample. The result is the optimal simulated path of *lev* over the sample period.

In practice, when considering measures of time-varying leverage, the problem is that we tend to get noisy signals of risk fluctuations. A major advantage of the empirical framework we introduce is that it exploits the cyclical properties of the elasticity-based indicators, while at the same time controlling for the noisy information they usually convey. Indeed, by computing optimal paths, the Kalman-filter smoothes the behaviour of our leverage series⁶.

4. Data and basic empirical facts

4.1. Data

Given the resemblance of the Canadian mandatory leverage with the leverage ratio requirement envisioned in Basel III, it is particularly instructive to analyze the influence of OBS banking on leverage cyclicity using a Canadian dataset. Note that this choice also provides a way to directly account for the regulatory capital arbitrage associated with the enforcement of a leverage requirement (Calomiris and Mason 2004, Ambrose et al. 2005, Brunnermeier 2009, Kling 2009, Cardone-Riportella et al. 2010, Nijsskens and Wagner 2010).

Statistics Canada provides no comprehensive database on bank financial results. Bankscope and Bloomberg offer statistics on bank financial results, but the series cover

⁶ We checked the robustness of our results with the conditional approach as described in Appendix 1. Since the message is basically the same, the associated results are not reported. However, in the empirical section, we discuss the results obtained using this method for the degree of total leverage (*DTL*).

only a short period of time. We thus build the relevant data recorded over the years from the various associations and institutes providing data, in particular the Canadian Bankers Association and the Office of the Superintendent of financial institutions⁷. Our quarterly series are available for the eight major banks, which account for more than 90% of the Canadian banks aggregate assets, and cover a sample period running from the first quarter of 1997 to the first quarter of 2009.

This dataset indicates a relatively low risk level for the Canadian banking system (Ratnovski 2009, Bordo 2011), a specificity due to the banks funding structure. Compared to the international representative bank, Canadian banks fund more of their operations with retail deposits relative to wholesale funding. This particular funding structure contributes, *ceteris paribus*, to decrease bank risk exposure to external shocks. In this respect, Canadian data appear particularly well-suited to isolate the impact of market-oriented activities on leverage cyclicity.

4.2. Stationarity and detrending

To properly construct our elasticity-based indicators, we need to examine the degree of integration of the series involved in order to work with stationary series. We first rely on the Augmented Dickey-Fuller unit root test with a deterministic trend to the series. The tests fail to reject the null hypothesis of the presence of a unit root, even when we add a deterministic trend (Table 1). Incidentally, this might signal the presence of a stochastic trend in the series, and it thus seems preferable to detrend the series with several techniques.

Insert Table 1 here

⁷ We are very grateful to Bank of Canada's economists Étienne Bordeleau and Céline Gauthier for providing their data.

In this regard, note that if the time series entering the computation of our elasticity constructs were not properly detrended, the X/Y ratio could completely dominate the cyclical part. In this case, the elasticity computation delivers hardly interpretable results, especially if we are interested in the fluctuations in bank risk captured by the derivatives. Hence, we have to address the question of detrending carefully. For the sake of robustness, since the detrending method influences the leverage dynamics, we need to consider several detrending methods (Canova 1998). We begin with a conventional leverage detrending method, the logarithmic residuals detrending method. Following DeYoung and Roland (2001) methodology, we compute the elasticity of the variable Y with respect to the variable X by first detrending the series with the following set of regressions:

$$\log(Y_t) = \alpha_0 + \alpha_1 trend + \varepsilon_t, \quad t = 1, 2, \dots, T \quad (13)$$

$$\log(X_t) = \beta_0 + \beta_1 trend + \mu_t, \quad t = 1, 2, \dots, T \quad (14)$$

where *trend* is a deterministic trend variable scaled from 1 to T . Then, we run an ordinary least squares (OLS) regression on the residuals to obtain the elasticity coefficient:

$$\varepsilon_t = \lambda_0 + \theta \mu_t + \xi_t \quad (15)$$

where the estimated $\hat{\theta}$ measures the elasticity of Y to X .

Compared to previous studies, we apply a variety of detrending filters, and in particular the Hodrick-Prescott (HP) detrending method, because our main objective is to analyze leverage at business cycle frequencies. As a robustness check, we also consider other detrending methods, including the level-cubic method, the log-cubic detrending method and the first-differences⁸.

⁸ In general, the HP filter tends to deliver robust cyclical properties. The results relative to the other detrending methods are reported in Appendix 2.

4.3. Leverage magnitudes

In general, the signs of our measures are robust to the detrending method used, but the average leverage levels can be somewhat sensitive to the detrending method (Table 2). For example, using the simple logarithmic residuals method, *DTL*, the elasticity of net earnings to total income ($\xi_{earn-totinc}$), is 1.14, while it is equal to 2.08 with the HP method. To explain this difference, note that the conventional logarithmic residuals detrending method is based on the residuals of the regression of the series logarithms, so it does not fully account for the series growth rates nonlinearity compared to more sophisticated detrending methods.

Insert Table 2 here

More importantly, note that the estimated coefficient of the degree of total leverage ($\xi_{earn-totinc}$) is significantly greater than 2 when using the HP method. This result suggests that bank risk is generally quite high over the 1997-2009 sample period. By comparison, the estimated “balance sheet” elasticity-based leverage measure associated with the traditional indicator, i.e. the elasticity of equity to assets ($\xi_{eq-assets}$), appears much lower than one. More precisely, without detrending, this elasticity measure, which is then basically the conventional measure of bank risk, is close to 1, but once detrended, it is equal to 0.18 using the HP filter, and to 0.58 with the simple logarithmic residuals detrending method. In other words, contrary to a broad leverage measure, the level of risk implied by the traditional measure is too low. This low leverage value might partly relate to uncaptured nonlinearities in bank balance sheet data. However, considering the in-

crease in bank systemic risk observed throughout the sample period, this low level also supports the idea that the traditional measure of leverage does not fully capture bank risk.

In this respect, the time-varying regulatory measures which partly account for OBS banking seem more appropriate. For example, the elasticity-based mandatory leverage (ζ_{manda}) is higher than its ratio counterpart. However, note that this type of measure also remains lower than one. With the Hodrick-Prescott detrending method, the estimated elasticity-based mandatory leverage is only equal to 0.45, compared to 2.08 for the *DTL* measure. This basic observation constitutes a first indication that *DTL* might better detect bank risk than Basel III-type leverage. This should be expected since, contrary to the latter, *DTL* accounts for all market-oriented banking activities, including the riskiest ones.

4.4. The Kalman-filtered *DTL* series

As in previous studies, so far we have only considered average measures of leverage. An implicit assumption underlying this standard approach is that banks have a stable product-mix and stable parameters values describing their behaviour. However, this assumption might appear restrictive because, in the context of market-oriented banking, bank actual leverage tends to fluctuate more in tandem with the business cycle (Shin 2009). In this paper, one of our primary objectives is to provide a new approach relaxing this assumption to rigorously account for leverage dynamics.

To implement the Kalman filter with the logarithmic residuals detrending method, the measure equation (equation (4)) has to be transformed into equation (15), with a time-

varying θ computed with the Kalman filter such that:

$$\varepsilon_t = \lambda_0 + \theta_t \mu_t + \xi_t \quad (16)$$

To be consistent with the recent banking history, we expect our Kalman-filtered, elasticity measures of leverage to be on an upward trend after the Asian crisis and until the subprime crisis, as systemic risk increases worldwide during this period (Rajan 2005, Blanchard 2009, Rajan 2009, Adrian and Shin 2010, Barrell et al. 2010, Calmès and Théoret 2010, Nijskens and Wagner 2010). Figure 8 displays the Kalman-filtered bank leverage measured with the non-detrended and detrended elasticities of *DTL*. First note that, if not properly detrended, the measure has a pattern similar to the traditional assets to equity measure of leverage. As expected, it is relatively stagnant during the period associated with the development of shadow banking (2000-2007), and collapses during the 2007 subprime crisis (i.e., a severe deleveraging episode). However, when detrended with the simple logarithmic residuals method, the *DTL* elasticity measure sharply increases after 2002. After the Asian crisis, detrended *DTL* presents a period of steady increase which is only interrupted in 2005⁹ and during the 2007 subprime crisis. Note that this pattern is robust to the choice of the detrending method used. For example, with the HP filter, *DTL* similarly detects the increase in systemic risk observed during the sample period. This finding is also robust to the way leverage is smoothed. Indeed, the behaviour of the conditional version¹⁰ of *DTL* delivers results comparable to its Kalman filter counterpart, except that it is more volatile and that the deleveraging process associated with the subprime crisis seems more pronounced.

Insert Figure 8 here

⁹ A year associated with creative accounting and the Enron's episode.

¹⁰ For more details see Appendix 1.

4.5. *DTL versus the benchmark measures*

The Kalman filtered elasticity of equity to assets captures the deleveraging process associated with the Asian crisis¹¹, and the releveraging which follows until the economic slowdown of 2002 (Figure 9). Nevertheless, its overall behaviour resembles the quite anemic pattern of the traditional leverage ratio. In this sense, the outperformance of the *DTL* measure cannot only be attributed to the way it is built, but also to the fact that it better encompasses embedded and economic leverages. *DTL* also performs better than the elasticity-based mandatory leverage over the period 2000-2007 (Figure 10). Indeed, the elasticity-based mandatory leverage remains below 1, and relatively flat throughout the sample period. This pattern actually suggests that the upward profile of the mandatory ratio may simply reflect the increase in loan commitments and not the systemic risk build-up observed during the period.

[Insert Figures 9 and 10 here]

Finally, remark that compared to *DTL*, the elasticity-based mandatory leverage seems quite sensitive to deleveraging (Figure 10). Of course, we need to confirm this observation with a formal analysis (carried in the next section), but a priori this deleveraging sensitivity could be problematic for the Basel III leverage ratio requirement. Indeed, this ratio is not very different from the Canadian mandatory measure, except that it contains some securitization activities and defines capital in a narrower sense, (e.g., excluding

¹¹ Note that this measure might have also reacted to the VaR enforcement in 1998, following the 1996 amendment to Basel I, which required specific capital for market risk.

long-term debentures from capital). This slight difference could actually further accentuate the Basel III leverage sensitivity to deleveraging because banks might find harder adjusting their capital whenever the regulatory capital constraint binds¹².

5. The cyclicity of bank leverage

In this section, we cast bank leverage in a reduced form model to analyze the cyclical role played by OBS activities. We apply this model to the standard measures of leverage, namely the ratio of assets to equity and the mandatory leverage, to their corresponding Kalman filtered elasticity-based counterparts, and also to the Kalman filtered series of *DTL*.

5.1 The model

To study the determinants influencing leverage over the business cycle, in particular the impact of OBS activities and liquidity on bank risk-taking, we rely on a model in which leverage implicitly results from a trade-off between the expected growth of net worth and the risk associated with the net worth level (Shin 2009, Stein 2010) such that:

$$leverage = f \left[E(\text{growth}) \text{ of bank net worth, risk of bank net worth} \right] \quad (17)$$

where $f'_{E(\text{growth})} > 0$ and $f'_{risk} > 0$. The higher is the desired expected growth, the higher is leverage, and the higher is leverage, the higher is bank risk. Defined in this way, banks use leverage to amplify the impact of the factors determining expected growth, subject to

¹² Since debentures are arguably a more accessible source of funding than equity, banks will likely sell more assets, accelerating further the deleveraging process.

a level of manageable risk. In this framework, the desired growth of net worth is a function of both liquidity and OBS banking, such that¹³:

$$E(\text{growth}) = g[\text{liq}, \text{snonin}, \text{dlnactifs}] \quad (18)$$

where *liq* is the ratio of liquidity defined with respect to assets; *snonin*, the share of non-interest income (OBS generated); and *dlnactifs*, the annual growth rate of bank assets. The liquidity ratio should have a negative impact since a high liquidity ratio impairs growth and is also symptomatic of an episode of higher risk aversion. We can also anticipate that expected growth is positively related to the relative weight of OBS activities proxied by the share of noninterest income (*snonin*)¹⁴. Finally, the expected growth should positively comove with asset growth (*dlnactifs*). Indeed, an increase in asset growth should increase leverage because banks do not remain passive following changes in asset prices; they adjust their leverage to boost their net worth, which contributes to leverage procyclicality (Adrian and Shin 2010).

In the risk-growth trade-off defined in equation (17), the risk associated with banks' net worth is a function of liquidity and OBS banking such that:

$$\text{Risk} = h(\text{liq}, \text{snonin}, \text{llp}) \quad (19)$$

where *llp* are the loan loss provisions. When banks face increased credit risk, they have an incentive to lower their leverage to counter the mounting level of their *llp*.

The reduced form model deriving from equations (17) to (19) can thus be expressed as:

$$\forall t, (\text{leverage})_t = \beta_0 + \beta_1 \text{snonin}_t + \beta_2 \text{dlnactifs}_{t-1} + \beta_3 \text{llp}_t + \beta_4 \text{liq}_t + \beta_6 (\text{leverage})_{t-1} + \xi_t \quad (20)$$

¹³ When estimating the model, we also experimented with asset returns and spreads between the returns of assets and their funding cost, but the results were not significant. However, the liquidity ratio and *snonin* variables implicitly account for asset returns.

¹⁴ Indeed, banks resorted to OBS activities in great part to compensate for the decline of their traditional activities (Boyd and Gertler 1994, Calmès 2004).

where ξ_t is the innovation. The coefficient associated with $snonin$, β_1 , is expected to be positive since an increase in $snonin$ rises both expected growth and risk. Note however that this sign might be sensitive to regulatory capital arbitrage (Jones 2000, Calomiris and Mason 2004, Ambrose et al. 2005, Acharya and Richardson 2009, Kling 2009, Cardone-Riportella et al. 2010 and Nijskens and Wagner 2010). For example, for leverage measures based on balance sheet ratios, a negative sign for β_1 might suggest that banks actually engage in regulatory capital arbitrage, increasing their involvement in OBS activities to artificially decrease their observed leverage and dodge the capital requirement constraint. *A priori*, regulatory capital arbitrage should be at play when the regulatory constraint on capital becomes binding or near-binding, that is in expansion periods. In other respect, we expect a negative sign for β_4 . Indeed, in expansion, a decrease in liquidity should be associated with an increase in leverage because it increases expected growth, but at the cost of concomitantly increasing risk.

To characterize the cyclical influence of $snonin$ and liq on bank risk in the model, we decompose these two variables as follows:

$$snonin_t = I_{exp} snonin_t + I_{con} snonin_t \quad (21)$$

$$liq_t = I_{exp} liq_t + I_{con} liq_t \quad (22)$$

where I_{exp} is an indicator variable taking a value of 1 during expansion periods, 0 otherwise; and I_{con} is an indicator variable with a value of 1 during contraction periods, 0 otherwise. This decomposition helps capture the asymmetric impact of these two variables on leverage in expansion versus contraction. For example, following an increase in risk aversion, when banks deleverage and simultaneously boost their liquidity to avoid insolvency, we should expect a rise in the sensitivity of leverage to liquidity.

Insert Table 3 about here

5.2. The cyclical behaviour of the standard measures

Table 3 provides the OLS estimation of the model over the period 1997-2009 for the traditional and mandatory leverage measures. Overall, the performance of the estimation is quite good according to the adjusted R^2 , which range from 0.70 to 0.75. The residuals unconditional heteroskedasticity is treated with the White consistent covariance matrix, while the conditional heteroskedasticity, an overlooked problem with this kind of times series, is tackled with an EGARCH (1,1) process (Nelson 1991)¹⁵. There is no evidence of residuals autocorrelation, as suggested by the DW statistic. Over the whole sample period, with no cycle, the coefficient of *snonin* is negative for both the accounting and mandatory leverages. The estimated coefficient of *snonin*, significant at the 95% confidence level for both leverage series, is equal to -5.45 for the traditional leverage and to -4.05 for the mandatory measure. This indirectly supports the idea that banks might indeed rely on OBS activities to engage in regulatory capital arbitrage (Nijskens and Wagner 2010).

More importantly, note that the asymmetry related to the phase of the business cycle differs for the two measures. For the traditional leverage, the *snonin* coefficient, significant at the 95% confidence level, is equal to -3.25 in expansion, and to 3.80 and insignificant in contraction. This suggests that, as expected, banks are more involved in regulatory arbitrage in expansion. However, the estimated coefficient of *snonin* for the

¹⁵ We tried different forms of GARCH processes, like the simple GARCH(p,q), with various lags, and EGARCH(p,q), and TARARCH(p,q) processes to account for the asymmetries in residuals. The EGARCH(1,1) gives the best results in terms of the fit of the equations. The standardized residuals are normal, or near-normal after controlling for the conditional heteroskedasticity problem with the EGARCH(1,1), which is not the case with other forms of GARCH processes. For the tests related to the selection of a GARCH process see Franses and van Dijk (2000).

mandatory leverage is only significant in contraction, its estimated level being -5.42. This counterintuitive result is attributable to the fact that, as the Basle III leverage requirement, the Canadian mandatory leverage includes a fraction of OBS activities, notably credit commitments. In contraction, on-balance-sheet assets rebalance, securitization decreases and loan commitments are exercised and repatriated on balance sheet as loans¹⁶. Because of this feedback effect, the mandatory leverage strongly signals deleveraging in contraction. This asymmetric effect might explain why the mandatory leverage appears so sensitive to deleveraging (Figure 10).

In other respect, note that the estimated coefficients of the liquidity ratio are quite similar for both the traditional and mandatory measures, being respectively -37.73 and -35.61, both significant at the 99% confidence level. However, similar to what we observe with the *snoin* variable, the estimation seems to capture an asymmetric impact related to the phase of the business cycle, the asymmetry once again differing for the two measures of leverage, but in the opposite direction. On the one hand, the traditional leverage is more sensitive to liquidity in contraction than in expansion, the estimated coefficient being -37.69 in contraction, significant at the 99% confidence level, and -9.22 in expansion, significant at the 90% confidence level. In contraction periods, banks can hardly rely on their assets as collateral to extend their borrowings because of the important losses on assets they face. Hence, they have to increase their liquidity, while at the same time decreasing their assets to equity ratio to strengthen their balance sheet and regain profitability¹⁷. On the other hand however, contrary to the traditional leverage, the mandatory leverage is more sensitive to liquidity in expansion than in contraction. Since

¹⁶ Note that this process dampens the variations of the traditional leverage indicator.

¹⁷ In this respect, an increase in liquidity, like the injections performed by central banks during the subprime crisis, might ease the deleveraging process by fostering orderly sales of assets, as the gap between asset market value and their fundamental value can then be reduced (Uhlig 2010).

the need for narrow liquidity can be reduced with OBS activities, and since in expansion the opportunity cost imposed by the mandatory constraint becomes higher in terms of lost profits, it is not surprising to find that the mandatory leverage increases relatively more than the traditional indicator.

5.3 The cyclicalty of the benchmark elasticity-based measures

Insert Table 4 about here

Without cycles, *snonin* has a positive impact on $\xi_{eq,assets}$, its estimated coefficient being equal to 0.24 and significant at the 99% confidence level (Table 4). As for the assets to equity ratio, this impact seems greater in expansion (0.51) than in contraction (0.16), supporting the idea that OBS activities contribute more to bank risk in expansion than in contraction. Moreover, there is also a negative comovement between $\xi_{eq,assets}$ and the ratio of liquidity, the impact being more pronounced in expansion. By contrast, for the mandatory measure, the estimated coefficient of *snonin* in the ξ_{manda} equation is not significant. However, accounting for the phase of the business cycle, the estimated coefficient of *snonin* is again positive in expansion, equal to 1.58 and significant at the 95% confidence level.

More importantly, note that, contrary to all other leverage measures, ξ_{manda} reacts positively to the ratio of liquidity, the estimated coefficient of this ratio being equal to 10.36 in expansion and to 12.73 in contraction. This is a peculiar pattern because, as explained above, any increase in liquidity should lead to a decrease in bank risk. Intuitively, this discrepancy can be explained by the precautionary reserves banks hold as a buffer for their loan commitments exercise. In the Basel III-type indicators, these buffers play a

major role and has a dominant effect on the dynamic pattern of the series. In other words, this odd property is an artefact of the loan commitments dynamics, and it reinforces the idea that the Basel III-type indicators might actually deliver misleading results.

Insert Table 5 about here

5.4 The cyclical nature of the degree of total leverage

Table 5 reports our results for the *DTL* leverage measure when we apply the model (equation (20)) to the Kalman filtered measures obtained with the logarithmic residuals, i.e. simple logarithmic, and the HP detrending methods respectively. Compared to the standard measures of leverage, *DTL* seems more sensitive to regime changes. In the case of the simple logarithmic *DTL*, the R^2 increases from 0.55 to 0.72 and the *DW* statistic increases from 1.64 to 1.75; and in the case of the HP *DTL*, the R^2 raises from 0.62 to 0.76, while the *DW* increases from 1.60 to 1.85 when accounting for the cyclical phases.

Furthermore, as the elasticity-based mandatory leverage, *DTL* appears more sensitive to *snoin* in expansion than in contraction (Table 5). For instance, when using the simple logarithmic detrending method, the estimated coefficients are respectively 1.98 and 0.99, and significant at the 99% confidence level, and with the Hodrick-Prescott method, the corresponding coefficients are equal to 0.85 and -0.18, the first being significant at the 99% level while the second is insignificant at the usual confidence thresholds. This result suggests that a greater reliance on OBS activities directly increases the embedded leverage, and particularly so in expansion.

Finally, turning to the cyclical influence of liquidity on leverage, irrespective of the detrending method used, a decrease in the liquidity ratio leads to a greater increase in

DTL in expansion than in contraction (Table 5). For instance, using the simple logarithmic detrending method, a decrease in the ratio of liquidity increases *DTL* in expansion, while it decreases it in contraction, the coefficients being respectively -18.23 and 1.82, although the latter is not significant. Using the Hodrick-Prescott detrending measure, the corresponding coefficients are -23.99 and -5.66, respectively significant at the 1% and 10% levels. This result is consistent with the view that, thanks to OBS activities, banks can reduce their balance sheet liquidity ratio in expansion, hence accentuating actual leverage procyclicality.

6. Conclusion

In spite of the important impact of OBS activities on bank risk, papers focusing on bank OBS-induced leverage are quite rare. Yet, we argue that the kind of regulatory leverage to be implemented under Basel III is not necessarily a sufficient measure of bank risk. Judging by the Canadian experience with a similar measure, one important concern is that this type of indicators appears disproportionately sensitive to deleveraging. This is due to the type of OBS items the measures include, notably loan commitments. When credit commitments are exercised in contraction periods, *ceteris paribus*, it triggers a substantial decrease in the mandatory leverage.

The main results of this paper pertain to the cyclical pattern of bank leverage, which is generally better described when accounting for the influence of noninterest income and broad liquidity. We find that the asymmetric impact of liquidity on leverage is quite pronounced, compounding the procyclical effect of OBS banking. Indeed, the decrease in the balance sheet liquidity ratio associated with OBS activities tends to increase

the degree of leverage in expansion. More importantly, our results also suggest that the degree of leverage is particularly responsive to OBS activities in expansion.

This analysis leads to the natural conclusion that several measures of bank leverage should be considered to get a clearer picture of bank risk, as both detrending methods and the measures themselves provide complementary information on the stance of banking stability. In particular, it would be useful to consider indicators reflecting the whole spectrum of OBS activities. In this respect, the Kalman-filtered *DTL* indicator seems a direct way to control for regulatory capital arbitrage. By contrast, in its current version, the Basel III leverage requirement does not include components such as trading activities, securitization, and other business lines which may heavily contribute to bank risk procyclicality.

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Appendix 1

Computing time-varying leverage measures with the conditional approach

One conventional way of computing time-varying coefficients is the conditional approach (Ferson and Schadt 1996, Christopherson et al. 1998, Ferson and Qian 2004). In this respect, the Kalman filter method can simply be viewed as a smoothed version of this standard approach. Similarly to the Kalman filter, the conditional approach updates the coefficients each period following the arrival of new information. To cast the leverage equation in a conditional model, equation (4) is rewritten as:

$$\log(Y_t) = \lambda_0 + \theta_t \log(X_t) + \xi_t \quad (23)$$

Leverage, which is equal to θ_t in this case, is indexed by time to indicate that it is a time-varying coefficient conditional on the information set available at time t . Assume that θ_t is related to a vector of control variables \mathbf{Z}_t such that:

$$\theta_t = \psi_0 + \mathbf{Z}_t \boldsymbol{\omega} + v_t \quad (24)$$

where v_t is the innovation. To estimate the coefficients vector $\boldsymbol{\omega}$, we substitute equation (24) in equation (23), and equation (25) obtains:

$$\log(Y_t) = \lambda_0 + \psi_0 \log(X_t) + \mathbf{Z}_t \boldsymbol{\omega} \log(X_t) + \varsigma_t \quad (25)$$

Equation (25) is then estimated by OLS, and the coefficients of equation (24) are perfectly identified.

Appendix 2

Results robustness across varying detrending methods

Table 6 shares the structure of Table 2, but applying three other detrending methods to check the robustness of our basic empirical facts: the first-differences, the log-cubic and the level-cubic methods. In the first approach, the series are directly detrended using first-differences on the logged series, as often applied to non-stationary time series. Another standard procedure found in the literature resorts to polynomials detrending, for instance the cubic detrending method. As with the logarithmic residuals, the method is based on the following equations:

$$\log(Y_t) = \alpha_0 + \alpha_1 trend + \alpha_2 trend^2 + \alpha_3 trend^3 + \varepsilon_t, \quad t = 1, 2, \dots, T \quad (26)$$

$$\log(X_t) = \beta_0 + \beta_1 trend + \beta_2 trend^2 + \beta_3 trend^3 + \mu_t, \quad t = 1, 2, \dots, T \quad (27)$$

The elasticity coefficient is obtained by running an OLS regression on the residuals using equation (15). DeYoung and Roland (2001) provide a good example of the application of this technique to the study of bank degree of total leverage, although the authors rely on a modified version of cubic detrending to accommodate for the negative numbers associated with bank losses. More precisely, in their regressions, the variables are expressed in levels instead of logarithms¹⁸. The elasticity measure they derive from the residuals is defined as: $elasticity = \hat{\theta} \frac{\bar{X}}{\bar{Y}}$, where $\hat{\theta}$ is the estimated coefficient obtained from the residuals regression, and \bar{X} and \bar{Y} are respectively the mean values of X and Y computed

¹⁸ Note that the fact that their residuals are computed on variables expressed in levels instead of logarithms causes some problems when filtering, because the series ratio tends to fluctuate too much.

over the sample period. In our study we consider both cubic detrending methods to document the relative performance of the various leverage measures we analyze. To distinguish the DeYoung and Roland (2001) cubic detrending method from the regular logarithmic cubic detrending method, we call the former the level-cubic detrending method and the latter the logarithmic-cubic detrending method.

[Insert table 6 here]

A comparison of Table 6 to Table 2 confirms that, regardless of the detrending method, the average measures of leverage based on OLS are quite similar to those obtained with the Hodrick-Prescott method. In particular, the sign of the estimated coefficients is quite robust to the detrending method. But there are some differences however. For instance, the estimated elasticity-based mandatory leverages appear lower than those reported in Table 2. By contrast, one of the most popular leverage measures, the degree of total leverage displays very consistent results regardless of the detrending approach used. For four detrending methods, the estimated leverage, systematically significant at the 95% confidence level, remains in a narrow range, [2.18, 2.63], confirming the high degree of systemic risk involved in the sample period. Finally, note that the elasticity of equity to assets seems less robust than the other reported measures. In particular, the elasticity coefficient is no longer significant when using the first-differences and the level-cubic detrending method. Overall, these results suggest that it is preferable to rely on methods which best capture the nonlinearities associated with the growth of the series considered. In this respect, the HP and the log-cubic detrending methods seem to perform best, as well as the log-cubic detrending method, which gives similar results..

[Insert Figure 11 here]

In the literature, the first-differences method is the most recommended technique to tackle I(1) integrated variables, such as bank profit and revenue. However, the results are quite comparable to the former results, except maybe for the level-cubic detrending method which seems to deliver implausible results (Figure 11). Indeed, the DeYoung and Roland's (2001) approach has a tendency to capture time series fluctuations at very high frequencies and not business cycles fluctuations. To summarize, comparing Figures 8, 9 and 11, we can conclude that the HP and the log-cubic detrending methods deliver robust results and the most consistent estimators.

Tables

Table 1
Augmented Dickey-Fuller (ADF) unit root tests with a trend

	test <i>p</i> -value	ADF <i>t</i> -statistic	5% critical value	Series trend
Log assets	0.139	-3.010	-3.490	0.017***
Log equity	0.925	-1.060	-3.490	0.019***
Log noninterest income	0.480	-2.200	-3.490	0.012***
Log net-interest income	0.186	-2.840	-3.450	0.012***

Notes: The H0 hypothesis is the presence of a unit root. A *p*-value for the test greater than 0.05 signals the presence of a unit root at the 95% confidence level after correction for the trend in the logarithmic time series. Asterisks indicate the significance levels: * stands for 10%, ** stands for 5% and *** stands for 1%.

Table 2
 OLS estimation of the average elasticity-based leverage measures

	$\xi_{earn-totinc} (DTL)$	$\xi_{eq-assets}$	ξ_{manda}
Hodrick-Prescott			
coef.	2.08	0.18	0.45
<i>t</i>	4.78	2	3.94
<i>R</i>²	0.23	0.05	0.22
<i>DW</i>	2.06	0.61	0.42
Simple log. residuals			
coef.	1.14	0.58	0.97
<i>t</i>	2.57	1.85	12.44
<i>R</i>²	0.08	0.19	0.63
<i>DW</i>	1.18	0.43	0.57
No detrending			
coef.	1.25	1.11	0.85
<i>t</i>	3.44	42.44	31.68
<i>R</i>²	0.47	0.95	0.95
<i>DW</i>	1.86	0.54	0.32

Notes: $\xi_{earn-totinc}$: elasticity of net earnings to total income;; $\xi_{eq-assets}$: elasticity of equity to assets; ξ_{manda} , elasticity-based mandatory leverage. Residuals autocorrelation is controlled with autoregressive terms, and residuals conditional heteroskedasticity is treated with EGARCH (Nelson 1991).

Table 3
Assets to equity ratio versus mandatory leverage

	Accounting leverage		Mandatory leverage	
	no cycle	with cycles	no cycle	with cycles
<i>c</i>	29.03	12.20	23.81	22.67
	<i>11.35</i>	<i>16.49</i>	<i>13.72</i>	<i>253.88</i>
<i>snoin</i>	-5.45		-4.05	
	<i>-2.21</i>		<i>-2.12</i>	
<i>I_{exp}snoin</i>		-3.25		-0.74
		<i>-3.38</i>		<i>-0.44</i>
<i>I_{con}snoin</i>		3.80		-5.42
		<i>1.23</i>		<i>-2.90</i>
<i>liq</i>	-37.73		-35.61	
	<i>-3.93</i>		<i>-4.23</i>	
<i>I_{exp}liq</i>		-9.22		-40.73
		<i>-1.66</i>		<i>-6.86</i>
<i>I_{con}liq</i>		-37.69		-22.62
		<i>-2.86</i>		<i>-3.60</i>
<i>dlnactifs_{t-1}</i>	0.03	0.05	0.02	0.01
	<i>1.33</i>	<i>4.95</i>	<i>1.76</i>	<i>0.88</i>
<i>llp</i>	0.30	-0.43	-0.75	-0.50
	<i>0.54</i>	<i>-0.87</i>	<i>-2.08</i>	<i>-1.30</i>
<i>y_{t-1}</i>	0.94	0.56	0.59	0.73
	<i>13.05</i>	<i>17.79</i>	<i>7.14</i>	<i>7.00</i>
R²	0.75	0.71	0.70	0.73
DW	2.20	1.72	1.88	2.17

Notes: The dependent variables are accounting leverage, as measured by the ratio of assets to equity, and the Canadian mandatory leverage measure. The explanatory variables are: *snoin*: the share of noninterest income in net operating income; *liq*: a broad measure of bank liquidity; *dlnactifs_{t-1}*: the annual growth rate of bank assets lagged one period; *llp*: the ratio of loan loss provisions; *y_{t-1}*, the dependent variable lagged one period; *I_{exp}* an indicator variable taking the value of 1 in expansion and 0 in contraction; *I_{con}* an indicator variable taking the value of 1 in contraction and 0 otherwise. The residuals unconditional heteroskedasticity is accounted for using the White heteroskedasticity consistent covariance matrix. The conditional heteroskedasticity is treated with EGARCH(1,1) process (Nelson 1991). Coefficients *t* statistics are reported in italics.

Table 4
Elasticity of equity to assets and elasticity-based mandatory leverage

	Elasticity of equity to assets		Elasticity-based mandatory leverage	
	no cycle	with cycles	no cycle	with cycles
<i>c</i>	-0.15	-0.13	-0.64	-1.89
	-2.68	-7.41	-2.68	-2.92
<i>snonin</i>	0.24		0.40	
	3.38		1.57	
<i>I_{exp}snonin</i>		0.51		1.58
		13.22		1.97
<i>I_{con}snonin</i>		0.16		0.78
		5.93		1.25
<i>liq</i>	-1.15		5.40	
	-1.96		3.62	
<i>I_{exp}liq</i>		-6.4		10.36
		-8.86		2.74
<i>I_{con}liq</i>		0.51		12.73
		1.43		4.93
<i>dlnactifs</i>	0.16	0.17	0.01	-0.01
	2.28	4.81	3.79	-0.11
<i>llp</i>	0.11	0.11	0.03	0.46
	3.48	6.81	0.23	1.57
<i>y_{t-1}</i>	0.05	0.30	0.83	0.88
	1.27	5.86	25.86	13.74
<i>R²</i>	0.17	0.57	0.84	0.81
<i>DW</i>	1.45	1.71	0.77	1.55

Notes: See Table 3 for the definition of the variables. The series are the Kalman filtered HP detrended series. Due to its non-stationarity, the elasticity of equity to assets is expressed in first-differences. The residuals unconditional heteroskedasticity is accounted for using the White heteroskedasticity consistent covariance matrix. The conditional heteroskedasticity is treated with an EGARCH(1,1) process (Nelson 1991).

Table 5
The degree of total leverage (*DTL*)

	Simple log.		Hodrick-Prescott	
	no cycle	with cycles	no cycle	with cycles
<i>c</i>	-0.47	0.14	1.13	1.12
	-0.89	0.59	4.13	11.86
<i>snonin</i>	2.56		0.25	
	2.87		1.29	
<i>I_{exp}snonin</i>		1.98		0.85
		4.68		3.43
<i>I_{con}snonin</i>		0.99		-0.18
		2.68		-1.18
<i>liq</i>	-8.70		-10.59	
	-1.53		-5.13	
<i>I_{exp}liq</i>		-18.23		-23.99
		-5.54		-5.75
<i>I_{con}liq</i>		1.82		-5.66
		0.48		-1.72
<i>dlnactifs</i>	-0.95	-0.14	1.27	0.38
	-1.16	-0.34	3.01	0.92
<i>llp</i>	0.62	0.35	-0.46	-0.23
	2.22	2.95	-3.84	-1.18
<i>dum_crisis_2007</i>	0.59	0.37	0.13	0.14
	2.04	6.27	6.88	1.79
<i>y_{t-1}</i>	0.59	0.83	0.59	0.62
	4.24	9.72	9.13	9.44
<i>R</i> ²	0.55	0.72	0.62	0.76
<i>DW</i>	1.64	1.75	1.60	1.85

Notes: See Table 3 for the description of the variables. *Dum_crisis_2007* is a dummy variable taking the value of 1 during the 2007-2009 subprime crisis and 0 otherwise. The residuals unconditional heteroskedasticity is accounted for using the White heteroskedasticity consistent covariance matrix. The conditional heteroskedasticity is treated with an EGARCH(1,1) process (Nelson 1991).

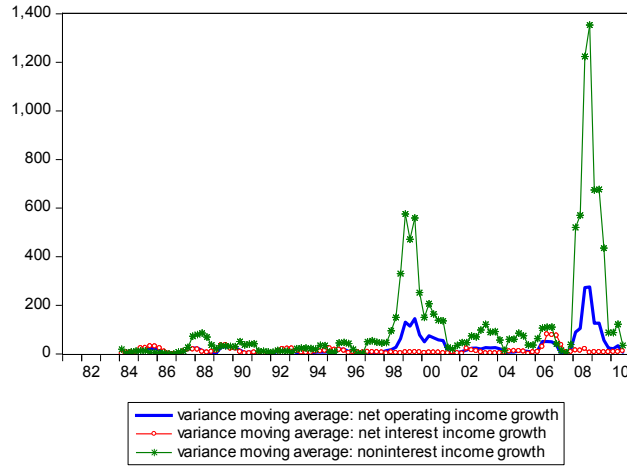
Table 6
 OLS estimation with alternative detrending methods

	<i>DTL</i>	$\xi_{eq-assets}$	ξ_{manda}
First-differences			
coef.	2.26	0.35	0.25
<i>t</i>	5.29	1.43	2.77
R^2	0.33	0.04	0.12
<i>DW</i>	2.28	1.69	1.27
Level-cubic detrending			
coef.	2.63	0.20	0.36
<i>t</i>	10.72	0.66	4.19
R^2	0.35	0.47	0.26
<i>DW</i>	1.66	1.56	0.64
Log.-cubic detrending			
coef.	2.56	0.10	0.17
<i>t</i>	16.18	3.13	1.65
R^2	0.22	0.43	0.03
<i>DW</i>	1.93	2.21	0.45

Note: This Table is a reproduction of Table 2 for three additional detrending methods, the first-differences, the DeYoung and Roland (2001) level-cubic and the log-cubic.

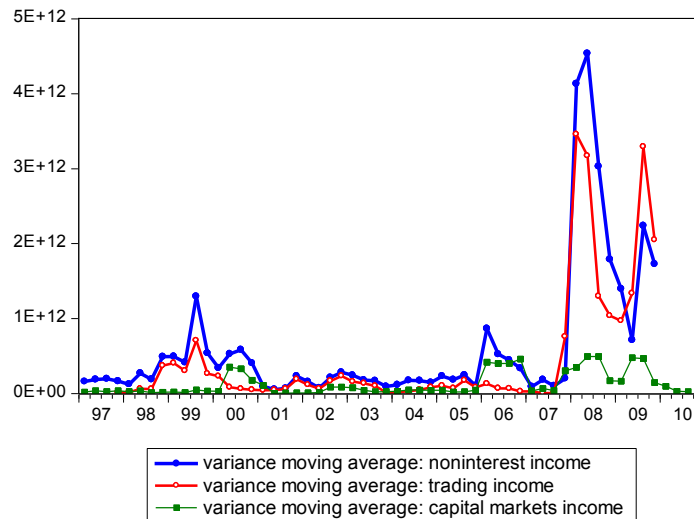
Figures

Fig. 1. Variance of net operating income growth and its components, 1983-2010



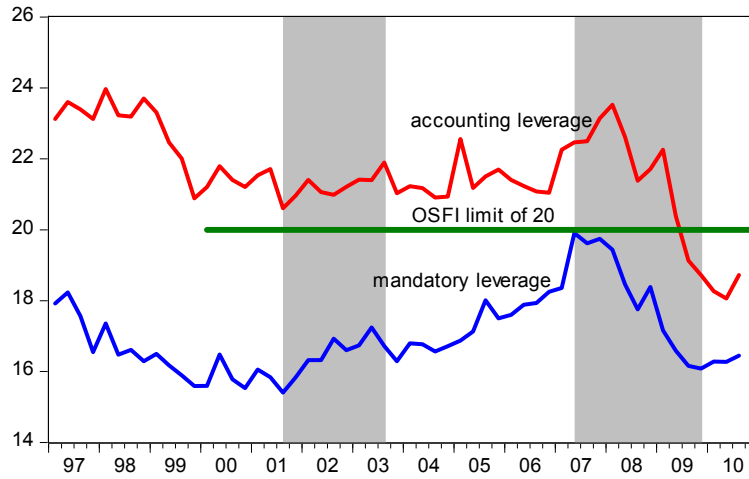
Note: The variance is a rolling variance computed over four quarters.
Source: Bank of Canada.

Fig. 2. Variance of noninterest income and of its two most volatile components, trading income and capital markets income, 1997-2010



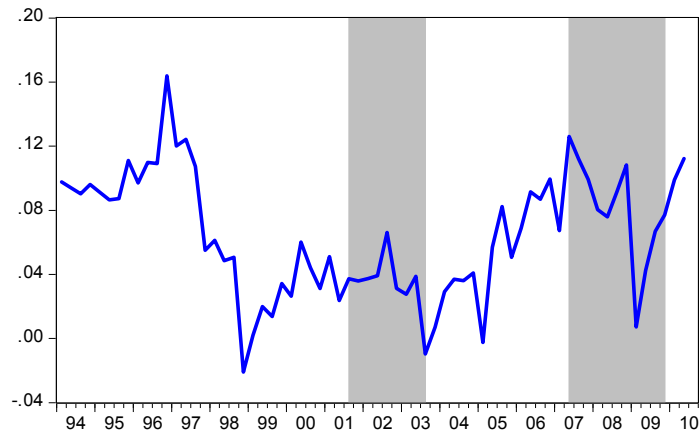
Note: The variance is a rolling variance computed over four quarters.
Source: Bank of Canada.

Fig. 3. Bank accounting and mandatory leverages



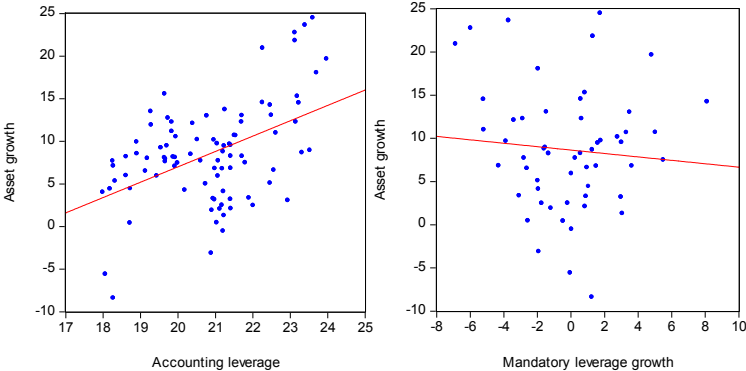
Notes: Shaded areas correspond to periods of contraction or marked economic slow-down.
Source: Bank of Canada.

Fig.4. OBS loan commitments in percentage of balance-sheet assets



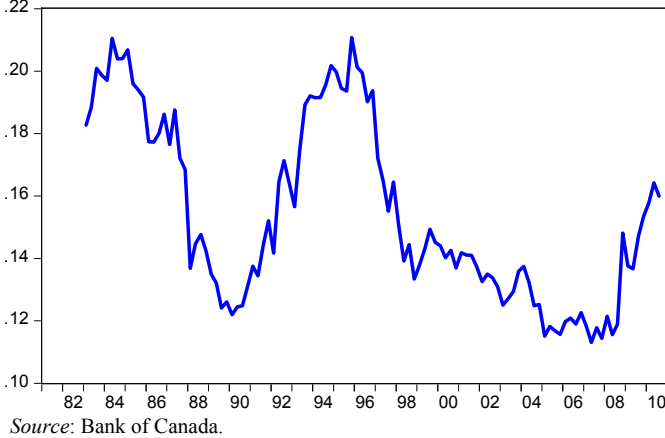
Note: Shaded areas correspond to periods of contraction or marked economic slowdown in Canada.
Source: Bank of Canada

Fig. 5. Asset growth versus leverage growth



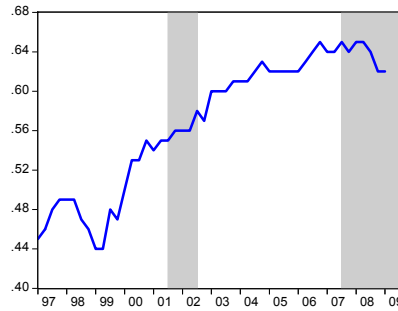
Source: National Balance Sheet Accounts, Statistics Canada, and Bank of Canada.

Fig. 6. Bank liquidity ratio



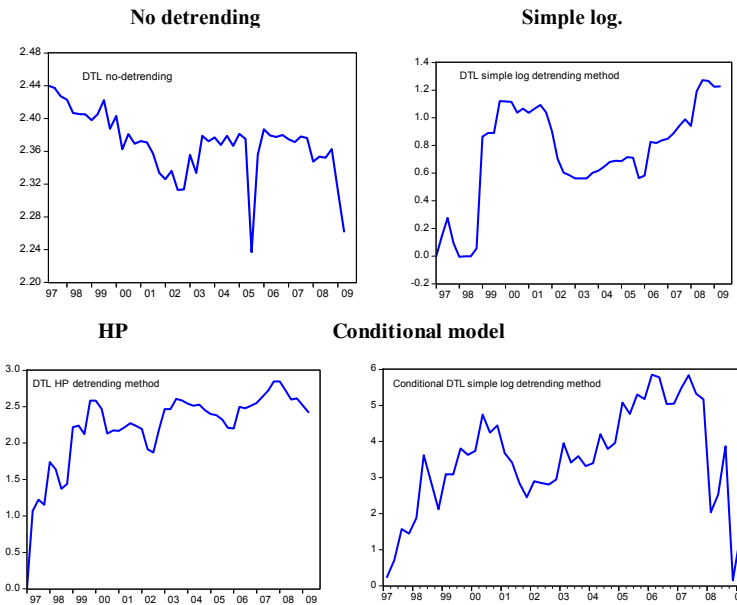
Source: Bank of Canada.

Fig. 7. Bank net leverage: (Debt - liquidity) / Assets



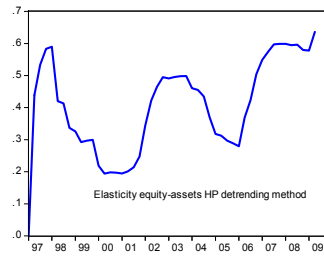
Note: Shaded areas correspond to periods of contraction or marked economic slowdown.
Source: National Balance Sheet Accounts, Statistics Canada, Bank of Canada.

Fig. 8. Kalman filtered degree of total leverage (*DTL*)



Notes: These figures are obtained by computing the elasticity of earnings to net operating income (*DTL*) using the Kalman filter procedure related in the article. Earnings and net operating income series are detrended using the two methods described in section 4. Conditional *DTL* is computed using equation (25) and the simple logarithmic detrending method.

Fig. 9. Kalman filtered elasticity of equity to assets



Note: This elasticity measure is obtained using the Kalman filter procedure. The series is detrended using the Hodrick-Prescott filter.

Fig. 10. Degree of total leverage versus elasticity-based mandatory leverage

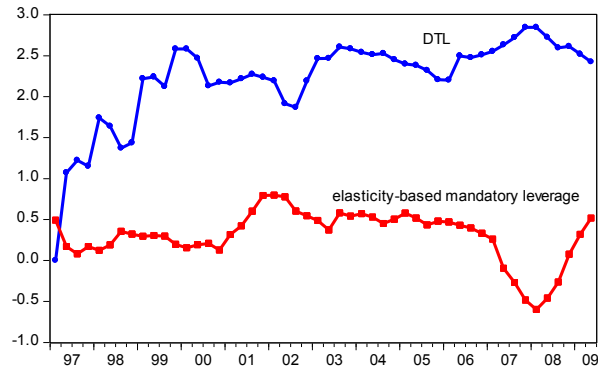
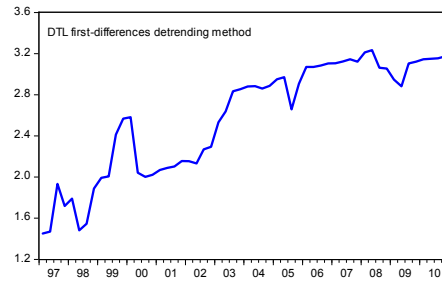
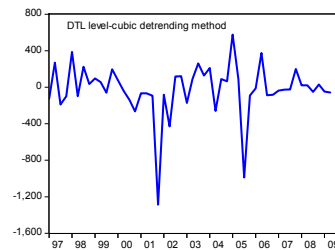


Fig. 11 Kalman filtered *DTL* using other detrending methods

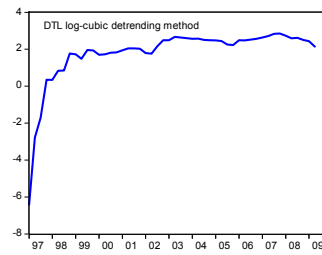
First-differences detrending method



Level-cubic detrending method



Log-cubic detrending method



Note: Elasticities are obtained with the Kalman filter procedure.