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JEL Classification: G13; G21.

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Does the GARCH Structural Credit Risk Model Make A Difference?[‡]

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I. Motivation

In the empirical option pricing literature, it's a well-known fact that the observed implied volatility smile in option prices does not correspond to the assumption of constant return volatility in the Black-Scholes (1973) model. Out-of-the-money call or put prices are typically higher as compared to the Black-Scholes formula. For equity options the smile is skewed and more looks like a smirk, indicating that in particular out-of-the-money put prices are substantially higher as compared to the Black-Scholes formula. In other words, the risk-neutral densities implied out from equity option prices are left-skewed and leptokurtic rather than normal. One possible solution could be to allow volatility to be time varying, which generates the fatter tails in the multi-period return distribution. Additionally, allowing the returns to be negatively correlated with the volatility process generates the negative skewness. Consequently, asymmetric stochastic volatility models have been quite successful in the empirical option valuation literature (see among others Heston (1993), Duan (1995), Heston and Nandi (2000), Lehnert (2003) and Bams et al. (2010)). The Heston (1993) model is a popular model in the continuous-time option valuation literature, while the NGARCH model of Duan (1995) is considered to be a standard model in the discrete-time literature. Both models contain stochastic volatility and a leverage effect. Heston and Nandi (2000) are 'bridging the gap' between the two streams in the literature, showing that Heston's (1993) model is the continuous-time limit of the Heston and Nandi (2000) model.

It was Merton (1974) who first adapted the Black and Scholes (1973) and Merton (1973) option pricing framework to the valuation of corporate securities. Since then, structural bond pricing models have been widely applied in both practice and academic research to value the risky debt of banks and firms. Structural credit risk models attempt to assess the creditworthiness of a firm by modeling the evolution of the firm's asset values as a stochastic process, and by viewing bankruptcy as an endogenous random event linked to the value of the firm's assets. In the "Merton model", instantaneous asset volatility is still constant by modelling. However, similar to equity returns, the actual distribution of the underlying asset value often has a fatter left-hand tail and a thinner right-hand tail than the normal distribution. In practice, however, the time series of asset

values of the firm, and the volatility of asset returns, cannot be observed directly, and must be inferred from the time series of equity values. Typically, firms experience periods of great uncertainty about growth rates of firm's assets vis à vis periods of relative tranquillity. As a result, the calibrated asset return volatility is found to be significantly time varying suggesting that the volatility of firms asset returns is stochastic. In order to deal with this feature, Malone et al. (2011) propose a structural credit risk model with asset return volatility following a GARCH process of Heston and Nandi (2000) type. Using simulated data, they find that their model outperforms the standard Merton (1974) and the Duan (2004) maximum likelihood estimation of the model.

In this study, we empirically investigate and evaluate various approaches to structurally assess credit risk using a panel of European banking groups. We compare the GARCH credit risk model with different structural modelling approaches and evaluate their ability to correctly and timely assess the credit risk of a firm, e.g. by modelling the probability of firms' default (PDs). We consider not only the standard approaches in the literature, but also propose an alternative model that catches not only the timely credit events but also the steadily credit risk component which is potentially driven by economic variables. Models are evaluated by comparing their ability to timely identify changes in PD's. Three different methods are used. Firstly, causality tests are used to find the leading risk indicator. Secondly, a price discovery metric is constructed (based on Gonzalo and Granger's (1995)) to decompose the time series of PD's into permanent and transitory components, where the price discovery metric actually measures the contribution to the permanent component. Thirdly, a financial crisis event data set (2007-2009) is constructed and subsequently analyzed. It allows us to evaluate the relationship between the models predictions of PD measures and the influential events. The first evaluation method is more appropriate for testing the 'timeliness' of the models as indicators of the evolution of credit risk, while the latter two put more emphasis on testing the contribution of the models to identifying a 'fundamental' component of credit risk. Surprisingly, we find that the GARCH structural credit risk model, despite its more sophisticated modeling approach, typically underperforms more basic models. Importantly for macro-prudential policy, the combined Merton/GARCH-MIDAS model performs best and reflects important market events earlier than the other approaches.

The paper is organized as follows. Next section provides a brief discussion of the set of models used to estimate default likelihood. Section III discusses the data, and section IV the empirical results. Section V concludes.

II. Selected models to estimate default likelihood

This section briefly discusses the set of models used to compute default probabilities for the panel of European banks used in this study.

1. The Merton Model

In the Merton model, equity owners are viewed as holding a call option on the firm's value after outstanding liabilities have been paid off. They also have the option to default if their firm's asset value falls below the present value of the notional amount—or book value—of outstanding debt (“strike price”) owed to bondholders at maturity. In other words, when the market value of the firm's assets is less than the strike price, the value of equity is zero. Therefore, bond holders are viewed as writing a European put option to equity owners, who hold a residual claim on the firm's asset value if the firm is not going to default. Bond holders receive a put option premium in the form of a credit spread above the risk-free rate in return for holding risky corporate debt (and bearing the potential loss) due to equity owners' limited liability.

The market value of a firm's underlying assets is assumed to follow a geometric Brownian motion (GBM) of the form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \quad (1)$$

where V_A is the firm's assets value, with an instantaneous drift μ (the expected rate of return of the firm), and an instantaneous asset return volatility σ_A . W is a standard Wiener process. If X is the book value of the debt due at time T , Black and Scholes' formula provides the market value of equity, V_E :

$$V_E = V_A N(d_1) - X e^{-r(T-t)} N(d_2) \quad (2)$$

where: $d_1 = \frac{\ln(\frac{V_A}{X}) + (r + \frac{1}{2}\sigma_A^2)(T-t)}{\sigma_A \sqrt{T-t}}$, $d_2 = d_1 - \sigma_A \sqrt{T-t}$, r is the risk-free rate, and $N()$ is

the cumulative density function of the standard normal distribution. The probability of default (PD) of the firm is the probability that its assets' value will be less than the book value of its liabilities. The corresponding implied neutral probability of default is $\pi_N = N(-d_2)$. The "actual" probability of default is $\pi_A = N(-DD)$, where the distance-to-default, DD, is simply the number of standard deviations that the firm is away from default:

$$DD = \frac{\ln(\frac{V_A}{X}) + (\mu - \frac{1}{2}\sigma_A^2)(T-t)}{\sigma_A \sqrt{T-t}} \quad (3)$$

To get to "actual" PDs from risk-neutral PDs, the latter must be adjusted by the market price of risk, which is estimated using a capital-asset pricing model in this study:

$$u = \rho_{A,M} \frac{\sigma_A}{\sigma_M} (u_M - r) + r, \text{ where } \sigma_M \text{ is market asset return volatility, and } \rho_{A,M} \text{ is the}$$

correlation between firm's asset return and market asset return. Alternatively, historical recovery rates can be used to move from risk neutral to "actual" PDs. The derived "actual" PDs, however, could be still much higher than the observed default probabilities, the so-called "credit spread puzzle" (Huang and Huang, 2003). Moody's KMV instead maps distance to default into historical default probabilities. Chen, Collin-Dufresne and Goldstein (2009) try to adjust the level by calibrating pricing kernel to equity returns and aggregate consumption. A complication to calculate PDs is that the dynamics of the underlying asset value is not directly observable. To calculate σ_A , Moody's KMV iterative procedure is used.¹ For quoted financial institutions, the KMV approach implies

¹ Duan (1994) shows that the KMV iterative method is identical to maximum likelihood estimates (MLE).

taking daily equity data from the past 12 months to calculate historical assets volatility. Regarding the value of debt, the KMV approach takes all obligations due in one year, plus half of the long-term debt. The KMV method is a simple two-step iterative algorithm to solve for assets volatility. The procedure uses an initial guess for volatility to determine the asset value and to de-lever the equity returns. The volatility of the resulting asset returns is used as the input to the next iteration of the procedure which, in turn, determines a new set of asset values and hence a new series of asset returns. The procedure continues in this manner until it converges.

2. The combined Merton and GARCH-MIDAS Model

The KMV approach of using a 12-month window of daily equity data to estimate σ_A , while practical, may not be appropriate e.g. for a central bank interested in assessing financial stability over time, as the resulting PDs may not track risk timely. To cope with this handicap, at least partially, this study uses a straightforward result from the Merton model, i.e., that the volatility of the firm's assets and its equity are related by the following optimal hedge equation: $\sigma_E = \left(\frac{V_A}{V_E}\right) \frac{\partial V_E}{\partial V_A} \sigma_A$. As a result, asset values and asset volatilities can be directly estimated by simultaneously solving this optimal hedge equation and the call option equation. In this manner, it is feasible to get timely default likelihood indicators by choosing the short-run and long-run components of equity volatility. For this purpose, Engle, Ghysels and Sohn (2008)'s class of GARCH-MIDAS² models is preferred. GARCH-MIDAS distinguishes short-and long-run sources of volatility and could also link them directly to economic variables. In this study, the GARCH-MIDAS model with rolling window realized volatility (RV) is estimated (the option using macro variables is not explored here).³

² GARCH-MIDAS accounts for generalized autoregressive conditional heteroskedastic models using mixed data sampling.

³ Ongoing separate research includes using the Merton and the GARCH-MIDAS models together not only to capture changes in PDs more timely, but also to model the macro financial factors underlying credit risk.

In the GARCH-MIDAS model with rolling window RV, the return on day i is written as: $r_i = \mu + \sqrt{\tau_i g_i} \varepsilon_i$, where volatility has two components, namely g_i , which accounts for short-lived daily fluctuations, and a secular component τ_i for all $i = 1, \dots, N$, and $\varepsilon_i | \Phi_{i-1} \sim N(0, 1)$ with Φ_{i-1} the information set up to day $(i - 1)$. The volatility of the short-term component g_i is a GARCH (1,1) process modeled by Engle *et al* (2008) as:

$$g_i = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1} - \mu)^2}{\tau_i} + \beta g_{i-1} \quad (4)$$

Similarly, the long-run τ_i component is estimated by smoothing rolling window realized volatility:

$$\tau_i = m + \theta \sum_{k=1}^K \varphi_k RV_{i-k} \quad (5)$$

where φ_k is a smoothing function and $RV_i = \sum_{j=1}^{N'} r_{i-j}^2$. The time span N' can be monthly, quarterly, or biannual at $N' = 22$, $N' = 65$ or $N' = 125$ respectively. K is determined by ‘MIDAS lag years,’ spanned in each MIDAS polynomial specification for τ_i . Since the PDs are estimated monthly in this study, a monthly time span and one MIDAS lag year are used not only to catch credit events timely but also to compare with the Moody’s KMV iterative procedure which typically takes daily equity data from the past year to calculate asset return volatility.

The GARCH-MIDAS is estimated by Quasi-maximum likelihood first, and then the conditional short-run or long-run variance forecasts on day $i+1$ are used to calibrate the PD by the above-mentioned two equations on day i : thus, the component dynamic volatilities will ideally make the Merton model’s PDs less backward looking than the estimation of volatility using the KMV approach. The component dynamic volatilities also imply the component dynamic PDs estimated by the Merton model. So Merton

GARCH-MIDAS catches credit events not just timely, but also catches the steady credit risk component which is potentially driven by economic variables.

3. The Heston & Nandi GARCH Structure Model

Even when the Merton model is combined with the Engle *et al.*'s GARCH-MIDAS model in a two-step approach, instantaneous asset volatility is still constant by modeling. However, similar to equity returns, the actual distribution of the underlying asset value often has a fatter left-hand tail and a thinner right-hand tail than the lognormal distribution. This will happen e.g. if volatility is stochastic and negatively correlated with the price of the underlying asset. Many existing empirical studies have shown the importance of time-varying volatility, the leverage effect, negative skewness and the existence of a “volatility smile”. The approaches followed in the literature to deal with that modeling pitfall have been to either model volatility stochastically or to assume *ex-ante* a price probability distribution that is compatible with the alluded observed regularities (e.g., a mixed-log normal distribution). Alternatively, a GARCH structure option model with a closed-form solution has been proposed by Heston and Nandi (2000). To our knowledge, this is the first model to provide a readily computed option formula for a random volatility model that can be estimated and implemented solely on the basis of observables. In addition, endogenizing GARCH-like time-varying volatility directly into a structure model would enable to identify changes in PDs earlier than by using the Merton model, a feature that commands a premium in the task of designing financial stability measures.⁴

According to Heston and Nandi (2000), the log return R of the firm's asset value follows a particular GARCH process:

⁴ Using S&P500 index options, Heston and Nandi (2000) show that the out-of-sample valuation errors from the single lag version of their GARCH model are substantially lower than those from the ad-hoc Black and Scholes model of Dumas, Fleming and Whaley (1998) that uses a separate implied volatility for each option to fit to the smirk in implied volatilities. The GARCH model remains superior even though the parameters of the GARCH model are held constant and volatility is filtered from the history of asset prices while the ad-hoc Black and Scholes model is updated every period. They attribute the improvement largely to the ability of the GARCH model to simultaneously capture the correlation of volatility with spot returns and the path dependence in volatility.

$$\begin{aligned} R_{t+1} &= \ln(V_{t+1}/V_t) = r + \lambda h_{t+1} + \sqrt{h_{t+1}} z_{t+1} \\ h_{t+1} &= \omega + bh_t + a(z_t - c\sqrt{h_t})^2 \end{aligned} \quad (6)$$

where V_{t+1} denotes the underlying asset price, r the risk free rate, λ the price of risk and h_{t+1} the daily variance on day $t+1$ which is known at the end of day t . The z_{t+1} shock is assumed to be i.i.d. $N(0, 1)$. The Heston & Nandi model captures time variation in the conditional variance, and the parameter c captures the so-called “leverage”. The leverage effect refers to the observed negative relationship between shocks to returns and volatility which results in a negatively skewed distribution of returns. The market value of equity, V_E , has a formula similar to the Black and Scholes’ formula for call options: $V_E = V_A F_1 - X e^{-r(T-t)} F_2$, where F_1 and F_2 are risk-neutral probabilities which are derived from the moment generating function of the logarithm of the underlying asset price options.⁵ The difference with Black and Scholes’ formula is that Heston and Nandi’s depends on the current asset price and on the conditional variance $h(t + \Delta)$, itself a function of the observed path of the asset price. Therefore, volatility is a readily observable function of historical asset prices. The implied neutral probability of default is $1 - F_2$. Since the underlying asset price is not directly observed, the GARCH structural credit risk model is estimated by the Expectation Maximization (EM) algorithm proposed by Malone, Rodriguez and Horst (2008). Similar to the KMV method, the EM procedure first uses an initial guess for the GARCH parameter vector to determine the asset values and to de-lever the equity returns by inverting the call option equation, compute the series of log returns from the extracted series of asset values, and then apply the Quasi-maximum likelihood method to estimate the new parameter vector of the GARCH process. The procedure continues in this manner until the chosen tolerance level for the convergence criterion is reached. To compare with the Merton model, a one-year rolling window of past daily equity returns is used to calculate the GARCH parameter vector, and considering all debt due in one year, plus half of the long-term debt as the strike price.

⁵ See Heston and Nandi (2000) equation (11) for the formula.

In the Merton model, once daily asset values are estimated, the drift μ can be computed by calculating the mean of log returns. However, in many cases, the actual return on assets can be negative. Similarly, the one-year rolling window might not be good enough to estimate the price of risk λ which is a crucial input to estimate the actual PD in the Heston & Nandi model. The expected rate of return can also be expressed as $\mu = r + (\rho_{A,M}(u_M - r)/\sigma_A\sigma_M)\sigma_A^2$ in the Merton model. In order to compare with the Merton model, the price of risk λ can be fixed by $\lambda = \rho_{A,M}(u_M - r)/\sigma_A\sigma_M$. The Heston & Nandi model with a fixed price of risk is estimated in this study.

4. The Geske Compound Option-based Structural Credit Risk Model

Previous models consider only a single debt maturity. However, debt maturity influences liquidity and the probability of default. This is an important drawback for e.g. a central bank or a supervisor interested in assessing and tracking banks' solvency. Geske (1977) and Delianedis and Geske (2003) consider a multi-period debt payment framework to which they apply compound option theory. This enables to account for the influence of the time structure of debt on the estimated PD.

Assume that a bank has long term debt, M_2 , which matures at date T_2 , and short term debt, M_1 , which matures at date T_1 . Between T_1 and T_2 , the Merton model is valid as the bank's equity equals a call option giving the shareholder the right to buy the bank at the second payment date, T_2 , by paying the strike price M_2 . If at date T_1 , the call option with the bank's value $\bar{V}$ equals at least the face value of the short term debt, M_1 :

$$M_1 = \bar{V}N(k_2 + \sigma_A\sqrt{T_2 - T_1}) - M_2e^{-r_{\bar{V}}(T_2 - T_1)}N(k_2) \quad (7)$$

then the bank can roll over its debt. So, the refinancing problem, the right to buy the simple call option of the second period by paying the strike price at the first payment date, is exactly a compound option as follows:

(8)

$$V_E = V_A N_2(k_1 + \sigma_A \sqrt{T_1 - t}, k_2 + \sigma_A \sqrt{T_2 - t}; \rho) - M_2 e^{-r_{F_2}(T_2 - t)} N_2(k_1, k_2; \rho) - M_1 e^{-r_{F_1}(T_1 - t)} N(k_1)$$

where $\rho = \sqrt{\frac{T_2 - t}{T_1 - t}}$, $N_2()$ is a bivariate cumulative normal distribution, and,

$$k_1 = \frac{\ln\left(\frac{V_A}{V}\right) + (r_{F_1} - \frac{1}{2}\sigma_A^2)(T_1 - t)}{\sigma_A \sqrt{T_1 - t}} \quad (9)$$

$$k_2 = \frac{\ln\left(\frac{V_A}{M_2}\right) + (r_{F_2} - \frac{1}{2}\sigma_A^2)(T_2 - t)}{\sigma_A \sqrt{T_2 - t}} \quad (10)$$

The richness of the model allows to calculate the following risk neutral PDs: (1) the total or joint probability of defaulting at either date T_1 or date T_2 , i.e., $1 - N_2(k_1, k_2; \rho)$; (2) the short-run probability of only defaulting on the short-term debt at date T_1 , i.e., $1 - N(k_1)$ and; (3) the forward probability held today of defaulting on the long-term debt at date T_2 , conditional on not defaulting on the short-term debt at date T_1 , i.e., $1 - \frac{N_2(k_1, k_2; \rho)}{N(k_1)}$. Similar to the Moody's KMV iterative procedure, the Geske model is

estimated by a two-step iterative algorithm. Regarding the maturity of value of debt, this study takes all short term obligations due in one year as a one-year maturity debt, and all long-term debt as a ten-year maturity debt.

III. Data

This study is applied to 20 major European banking groups (which have subsidiaries and branches active in Luxembourg). Market data used include daily government bond yield, S&P 500, equity prices, the number of outstanding shares, and book value data from Bloomberg. The short-term borrowings (BS047) and long-term debt (BS051) from

Bloomberg have annual, semi-annual, and quarterly data, however, which are not always consistent. To minimize inconsistencies, four filtering rules listed in Appendix A are used in this study. To get the “actual” PDs from risk-neutral PDs, the expected returns are estimated using a capital-asset pricing model. The implied equity risk premiums data (Damodaran 2011) are downloaded from Damodaran Online at <http://pages.stern.nyu.edu/~adamodar/>. The US market is assumed to characterize a mature equity market, and the stock market returns are represented by the returns on the S&P 500. The sample period is from May 30, 2000 to December 31, 2010. For evaluation, the list of the most important influential events in the period 2007 until 2009 is borrowed from Moreno and Peña (2011), and SEN 5YR CDS data from 2004 to September 2009 are downloaded from DataStream.

IV. Empirical Results

Results of the estimation of the four models described in the previous section are presented in several figures and tables. The purpose is twofold: first, to show how the estimated models can be used to build proxies of banks’ credit risk, without accounting for default dependency across financial institutions; second, to illustrate possible uses and differences across models of default that are important for assessing and tracking default risk paying particular attention at models’ capacity to anticipate credit risk changes.

1. Indicators of systemic banking risk

a. Asset-weighted PD index for Banking Groups (market-based models)

As in Jin and Nadal De Simone (2011), Figure 1 illustrates an indicator of systemic risk for banking. PDs from individual banks are put together in an index by aggregating the individual estimates weighted by their respective estimated implied asset values.⁶ The index tracks surprisingly well major events such as Lehman Brothers’ default and the sovereign crisis. In addition, consistent with all models results, it seems that the US

⁶ As in the Black-Scholes formula, the Merton model allows the estimation of implied asset values and implied asset volatilities.

Treasury Financial Stabilization Fund had a major positive impact on markets as since then, all PDs started falling.⁷ At the same time, note the evolution of the conditional probability of default on long-term debt that accompanied banks' efforts to increase the maturity of their debt profile and policy measures that increased banks' capital.

An important point to bring out from Figure 1 is the capacity of the Merton GARCH-MIDAS model to reflect important market events earlier than the other methods. This is the case, for instance, at the time of Lehman Brothers' default, and also later at the time of the sovereign distress started toward the end of 2009. As discussed above, this is the outcome of nesting GARCH-like time-varying volatility indirectly into the model structure (as mentioned above, volatility is still constant as in the Merton model).

b. Cumulative asset share and PDs.⁸

Figure 2 displays an indicator of banking system risk for the 20 banking groups using the Geske model and market information. It displays cumulative banks' implied asset values versus banks' PDs, sorted from lowest to highest. For example, at the end of 2008, 10 percent of the banking system had a short-term PD larger than 50 percent. The situation improved at end-2009 as 10 percent of the system had a short-term PD larger than 15 percent. At the end of 2010, the situation had further improved as 10 percent of the system had a short-term PD larger than 5 percent. The long-term PDs drop quickly in a similar pattern. Overall, "systemic risk"⁹ for the banking groups has continuously declined since 2008 to 2010.

c. Distance to distress

Another indicator of systemic risk is the distance to distress (DD). Figure 3 shows the DD for the 20 banking groups in the sample using formula (3). This is done for individual banking groups weighting the estimated DD by the respective estimated implied asset values. In addition, the portfolios of all banks are treated as "one bank" (the system) and

⁷ The Plan involved Treasury purchases of convertible preferred stock in eligible banks, the creation of a Public-Private Investment Fund to acquire troubled loans and other assets, expansion of the Federal Reserve's Term Asset-Back Securities Loan Facility (TALF), and other initiatives. The Fed also announced it would expand the TALF to as much to one trillion US dollars.

⁸ In the following sections, only neutral probabilities of default are used for the comparative studies.

⁹ As stated above, we do not model default interdependence.

the system DD is estimated. The difference between the system's DD and the average banking group's DD falls during periods of market stress, as it is the case, for example, since mid-2007. This suggests that the correlation among banks' PDs is increasing as it is normally the case during market stress periods.¹⁰

2. Indicators of banks' credit risk

Figure 4 displays an example of Deutsche Bank's estimated conditional short- and long-run components of the GARCH-MIDAS model using a monthly rolling window RV and one-year lag of RV's in the MIDAS filter. They are shown in standard deviation form and annualized. The specification of the GARCH process for short-run volatility is more sensitive to daily events, while the long-run component is driven relatively more by macroeconomic fundamentals. This is a useful feature for monitoring credit risk. Also, the combined model, GARCH-MIDAS plus Merton, lends itself to modeling the long-run component of PDs not only by showing the steadily accumulated credit risk, but also by improving its forecasting ability, as shown by Engle et al. (2008).¹¹

The asset-weighted PDs from the Heston & Nandi model does not apparently reveal market events earlier than the Merton model. However, the levels or severity are different, especially during the high-tech bubble and the recent financial crisis. The aggregate level might hide some important properties of this model. Figure 5a compares the results of the standard Merton model with those of the Heston & Nandi model for Deutsche Bank. As with other banking groups (not shown on the graph), an increase in Deutsche Bank's PDs accompanied the rise of tensions following the Lehman Brothers' event. As indicated earlier, traditional models tend to be backward looking, or rather the procedures to estimate volatility in those models, such as the KMV approach which uses 1-year rolling

¹⁰ Note that this is a lower-bound proxy for the System's DD as it is calculated without taking into account banks' default dependency.

¹¹ Engle et al. (2008) show that when the long-run volatility component is driven by output growth and inflation, their model out-performs traditional time series volatility models in out-of-sample forecasting. Even at short horizons, those macroeconomic variables play a significant role in explaining one-day ahead volatility prediction. This option is not explored in this paper. Ongoing separate research includes using the Merton and the GARCH-MIDAS models together, not only to capture changes in PDs more timely, but also to model the macro financial factors underlying credit risk.

volatility measures. While this can be improved upon by combining the Merton model with a GARCH-MIDAS structure as discussed above, results seem even better using the Heston & Nandi model due to its ability to simultaneously capture the volatility correlation with spot returns and volatility path dependence. Since volatilities from the Merton model look very smooth compared with those from the Heston & Nandi model, the Merton's PDs might miss some credit events as it is the case around November 2002, and in contrast, may exaggerate other credit events due to its cumulative nature as it is the case during 2009. Figure 5b shows another example for Deutsche Börse, in which the PDs from the Heston & Nandi model are much higher, and reflect market events somehow much earlier than those from the Merton model. Given that the Heston & Nandi model does not assume a normal distribution (shown not to be compatible with volatility regularities), it is theoretically expected to catch credit events more timely.

Table 2 reports the first four sample moments and the first order autocorrelation of PDs for the banking groups in the whole sample period from May 2001 to December 2010 and the more recent period from January 2004 to December 2010. They are consistent with the patterns displayed in Figure 1a. The average of PDs for the Merton model is similar to that for Geske's short-run, around 5 percent; it is 1 percent for Geske's long-run, and 6 percent for Geske's total. For the Heston & Nandi's model and for the Merton GARCH-MIDAS' long-run, the means are somewhat lower, 4 percent and 3 percent, respectively. Please note that the mean is not so meaningful for the Merton GARCH-MIDAS' short-run, since it is derived from annualized daily volatilities at the end of each month, and thus less autocorrelated.

The Kendall rank correlations of monthly PDs and PDs' changes between banking groups are shown on Table 3. They are strongly positively correlated, especially between the Geske's total, Geske's short-run, and Merton's. Overall, all models help us seeing the financial situation from different angles, putting the information together into a more vividly rich picture. First, the Merton model, a benchmark model, gives us a general PD indicator. Second, the Merton GARCH-MIDAS' short-run PDs helps us catch events more timely; while some might not be relevant to credit risk and die out quickly, the

long-run components collect the steadily accumulated credit risk. Third, when the crisis gets deeper, Geske's short-run and long-run PDs illustrate how the term structure of PDs evolves over time., Finally, the Heston & Nandi model could further help us adjust the expected severity of crisis and also potentially provide us an earlier financial stress warning.

Figure 6 plots the PDs using the Merton and Geske models applied to Banco Santander SA. As indicated before, the Geske's short-term PD tends to coincide with Merton's. They both track the crisis main events closely, including the additional market distress started toward the end of 2009 with the sovereign crisis. The value added of the Geske model, however, can be clearly illustrated by tracking the recent history of the bank. When Banco Santander launched a take-over in 2007, the conditional likelihood of defaulting in its long-term debt increased. It seemed to have raised further with the important expansion of Banco Santander in Europe in 2008 and in the US in 2009. It is noteworthy that the conditional probability increased at the same time the one-year likelihood of default was falling. This cannot be captured by the Merton model.

3. Models Comparison

Up to now, several measures have been proposed to track credit risk. By construction, the Merton GARCH-MIDAS model focuses on the term structure of volatility's impact on credit risk. The Geske model catches the term structure of default risk; while the Heston and Nandi model estimates the impact of stochastic volatility on PDs. In this subsection, we compare these informative models of default risk among themselves. We apply three methods, each of which stresses different features of the models' output: a causality test, a price discovery methodology, and an influential event study approach¹². The first evaluation method tests more the 'timeliness' aspect of the models' estimated PDs, while the latter two put more emphasis on the contribution of the models to identifying the 'fundamental' component of credit risk.

¹² See Moreno and Peña (2011), who use a similar approach in the context of systemic risk measures.

a. Causality Test

The Granger causality test (Granger, 1969) is used to identify a lead-lag relationship between the models' PDs predictions for each bank and, therefore, to choose a leading credit risk indicator. This test intuitively examines whether past changes in one variable, Y_t , help to explain current changes in another variable, X_t . If not, we conclude that Y_t does not Granger cause X_t . Formally, the Granger causality test is based on the following regression:

$$\Delta X_t = \alpha + \sum_{i=1}^p \beta_{xi} \Delta X_{t-i} + \sum_{i=1}^q \beta_{yi} \Delta Y_{t-i} + \varepsilon_t \quad (11)$$

where Δ is the first-difference operator and ΔX and ΔY are stationary variables. We reject the null hypothesis stating that Y_t does not Granger cause X_t if the coefficients β_{yi} are jointly significant based on the standard F-test. The lag length selection is performed using the Bayesian information criterion. To rank the measures, we give a score of +1 to measure Y if Y causes measure X and we give a score of -1 to measure X if X is caused by Y. The best measure gets the highest positive score, and the worst measure the highest negative score.

Table 4 summarizes the ranking scores of the Granger causality tests applied to each PD series individually based on the p-values at a confidence level of 1%. The upper panel shows the results for the 17 banking groups (three banks have zeros Geske's long-run PDs and have been dropped from the sample for this purpose) from May 2001 to December 2010. We get the same results using both the non-standardized and the standardized risk measures. The standardized measures are constructed with mean 0 and standard deviation 1. As expected, the Merton GARCH MIDAS' short-run PDs and Geske's short-run PDs rank as the best and second best leading measures, respectively, while the worst measure is Geske's long-run PDs. What is unexpected is that the Heston and Nandi model on average does not provide a leading indicator compared with the

Merton and the Merton GARCH MIDAS models, although it is theoretically expected to catch credit events more timely as discussed above. We also compare the PDs with the CDS Premium (SEN 5YR); see the lower panel for the 11 banking groups out of the banking groups in our sample that have issued CDS and have a long-enough number of data points, from January 2004 to September 2010. The CDS ranks as the best leading indicator whereas the rankings for others are similar as those displayed in the upper panel.

b. Price Discovery Analysis

The price discovery analysis (Gonzalo and Granger, 1995) allows us to determine, by using pairs of measures, which measure reveals fundamental information more efficiently. Formally, this price discovery methodology is based on the following factor model:

$$X_t = Af_t + \tilde{X}_t \quad (12)$$

The elements of X_t can be explained in terms of a small number of permanent components integrated of order 1, $I(1)$, $f_t = \gamma_{\perp}' X_t$, plus some $I(0)$ transitory components $\tilde{X}_t$. $\gamma_{\perp}$ can be estimated indirectly by the following VECM specification of vector X_t :

$$\Delta X_t = \gamma \alpha' X_{t-1} + \sum_{i=1}^p \Gamma_i \Delta X_{t-i} + \varepsilon_t \quad (13)$$

where X_t is a vector which includes a pair of credit risk measures, and ε_t is a white noise vector. The lag length selection is performed using the Bayesian information criterion. The parameter $\gamma = (\gamma_1, \gamma_2)$ is a vector including the parameters of the error correction term. Since the vector $\gamma_{\perp}'$ contains the coefficients that determine the market contribution to price discovery (permanent components). The market contribution to price discovery can be measured by the following price discovery metrics for the credit risk measure i , where $i=1, 2$

$$GG_1 = \frac{\gamma_1}{-\gamma_1 + \gamma_2}; GG_2 = \frac{-\gamma_1}{-\gamma_1 + \gamma_2} \quad (14)$$

Thus, we conclude that a given credit measure i contributes more to the fundamental component whenever its corresponding price discovery metric (GG_i , $i=1,2$) is higher than 0.5. The price discovery metric for an individual firm is truncated such that it has a lower bound of 0 and an upper bound of 1. To rank the measures, we give a measure a score of +1 if the measure gets values larger than 0.5 in the corresponding price discovery metric and a value of -1 if it gets values lower than 0.5.¹³

Table 5 summarizes the ranking scores which are based on the GG metrics. We also standardize all measures since the lower level of long-term PDs could draw too much weight on their contribution to the permanent component. The price discovery metric is used to decide which indicator plays an important role in identifying the fundamental component. Overall, and not surprisingly, the worst measures by the GG metrics are Merton GARCH MIDAS' short-run PDs and the CDS. The short-run component of the model is more targeted towards providing a timely risk indicator. The CDS could be noisy though a good leading indicator by causality tests. The rankings for the others are not very coherent, although we still find that the models with a long-run component are ranked higher on average, in particular the Merton GARCH MIDAS' long-run PDs. The Heston and Nandi model again is not doing a job as good as the Merton model, which is understood if we consider the dynamic volatility built in the Heston and Nandi model

c. Influential Events Analysis

Events analysis allows us to choose the more informative default indicators according to general influential credit events. The credit event variable we use is a dummy which reflects most important adverse news during the financial crisis. We apply the multinomial logit model, using each credit risk measure and its lags as explanatory variables, and choose the risk measures with the highest McFadden R-squared.

¹³ Detailed results are available upon request.

Given the monthly frequency of the measures, we construct the influential events variables on a monthly basis. The categorical variable ranges between 0 and 3, and it represents the number of events within the corresponding month (i.e., number 3 captures three or more events while 0, 1 and 2 capture the corresponding number of events). Our default indicators are monthly data at the end of each month. The event data set is constructed using all events happened within each month. So, the event data index is by construction more of a measure of systemic risk. Exposure to these systemic events can obviously be different across banks. However, major systemic events should have an impact on banks' default risk and, therefore, the results of the influential event analysis can be usefully compared with the price discovery analysis' results in the previous section. Usually the larger the number of lags used, the higher the McFadden R-squared; however, with more lags, the regressors matrix can more easily be singular or badly scaled. We select the number of lags subject to maximizing McFadden R-squared without loss of generality.

Higher values of McFadden R-squared indicate better model fitting. To rank the measures, we compare the McFadden R-squared by pairs and assign a score of +1 to the measure with the highest R-squared and -1 to the one with the lowest R-squared.

Table 6 summarizes the ranking scores using the McFadden R-squared criterion. Interestingly, the ranking scores are similar to those obtained using the GG metrics. Consistently, the Merton GARCH MIDAS' long-run PDs and Geske's long-run PDs rank as the best and second best measures, respectively, while the worst measure is the Geske short-run PDs. Heston and Nandi model still can't outperform the Merton model consistently, and CDS is in between, likely because the event data approach contains features consistent with timeliness and aggregate or systemic risk components.

IV. Conclusions and Policy implications

Since the pivotal work of Merton (1974), structural models have been widely applied in both practice and academic research to value the risky debt of banks and firms. The

importance of relaxing the Merton model's assumptions has long been discussed in the theoretical literature. In this study, we empirically investigate and evaluate various approaches to structurally assess credit risk using a panel of European banking groups. We compare the GARCH credit risk model with different structural modelling approaches and evaluate their ability to correctly and timely assess the credit risk of banks. Our evaluation methods include a test for the 'timeliness' of the models' risk indicator, as well as two methods that put relatively more emphasis on the capacity of the indicator of PD to identify 'fundamental' components of credit risk. Surprisingly, we find that the GARCH structural credit risk model, despite the more sophisticated modeling approach, typically underperforms more basic models. Interestingly, the combined Merton/GARCH-MIDAS model with a short- and long-run component of default risk generally performs best and reflects important market events earlier than the other approaches. This is a model that commands a premium for a macroprudential supervisor as, even without modelling banks' default interdependence, it is able to anticipate the deterioration in credit risk. It is, therefore, a tool to include in the arsenal of measures of banking sector stability.

An important extension to the work in this study is to identify the fundamental drivers of volatility as well as the drivers of short- and long-run PDs. This can be done using a large dataset of macroeconomic and financial variables such as it would be made possible using the framework offered by the generalized dynamic factor model. In addition, modelling banks' PDs interdependence could provide an even more timely and direct measure of the evolution of systemic risk. It is a well known that marginal PDs alone provide a downward-biased measure of systemic risk. These two avenues are currently being explored.

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Appendix

A. Filtering Rules for BS_ST_BORROW and BS_LT_BORROW:

The short-term borrowings (BS047) and long-term debt (BS051) from Bloomberg have annual, semi-annual, and quarterly data, however, not consistent. The four filtering rules are applied as followings:

- I. Take any zero as missing data.
- II. If the annual data exists and not equal to the semi-annual/quarterly data, then let semi-annual /quarterly data equal to the annual data. (Take annual data as trusted and priority data)
- III. If the annual data does not exist and both the semi-annual/quarterly data and annual data exist at the previous and next fiscal year, but semi-annual/quarterly data is very different from the corresponding annual data at the same previous and next fiscal year, then treat the semi-annual/quarterly as missing data. (To avoid untrusted semi-annual /quarterly data)
- IV. If the annual data does not exist and annual data exist at both previous and next fiscal year, but very much different from the semi-annual /quarterly data, then treat the semi-annual/quarterly as missing data. (To avoid untrusted and too choppy semi-annual /quarterly data between previous and next fiscal year)

**Figure 1 - Asset Weighted DP Index for Banking Groups
(Merton / Merton Garch-MIDAS / Heston & Nandi / Geske Model)**

**Figure 2 - Short-Term and Conditional Long-Term DPs of Banking Groups
(Geske Model, LT on RHS)**

**Figure 3 - Distance to Distress of Banking Groups
(Merton Model)**

Figure 4 - Conditional Short-run and Long-run Volatility of Deutsche Bank AG
GARCH MIDAS RW Model

**Figure 5a - DPs and Volatility of Deutsche Bank AG
(Merton and Heston & Nandi Models)**

**Figure 5b - DPs and Volatility of Deutsche Boerse AG
(Merton and Heston & Nandi Models)**

Table 1: List of Banking Groups

No.	Main Banking Groups	Location	Accounting Standard
1	Banco Santander SA	Spain	IAS/IFRS
2	BNP Paribas	France	IAS/IFRS
3	Commerzbank AG	Germany	IAS/IFRS
4	Credit Agricole SA	France	IAS/IFRS
5	Credit Industriel et Commercial	France	IAS/IFRS
6	Credit Suisse Group AG	Switzerland	US GAAP
7	Deutsche Bank AG	Germany	IAS/IFRS
8	Deutsche Boerse AG	Germany	IAS/IFRS
9	Deutsche Postbank AG	Germany	IAS/IFRS
10	Dexia SA	Belgium	IAS/IFRS
11	EFG Eurobank Ergasias SA	Greece	IAS/IFRS
12	IKB Deutsche Industriebank AG	Germany	IAS/IFRS
13	ING Groep NV	Netherlands	IAS/IFRS
14	Intesa Sanpaolo SpA	Italy	IAS/IFRS
15	KBC Groep NV	Belgium	IAS/IFRS
16	Landesbank Berlin Holding AG	Germany	IAS/IFRS
17	Mediobanca SpA	Italy	IAS/IFRS
18	Societe Generale	France	IAS/IFRS
19	UBS AG	Switzerland	IAS/IFRS
20	UniCredit SpA	Italy	IAS/IFRS

Notes to Table: This table shows the 20 European banking groups, which have 33 subsidiaries and branches active in Luxembourg. The 33 subsidiaries and branches registered in Luxembourg represent about two thirds of the total assets of the Luxembourg banking industry.

Table 2: Descriptive Statistics of Asset-Weighted PDs of Banking Groups

5/31/2001 - 12/31/2010							
	Merton	Merton Garch- MIDAS ST	Merton Garch- MIDAS LT	Geske Total	Geske ST	Geske LT	Heston & Nandi
Mean	0.05	0.03	0.03	0.06	0.05	0.01	0.04
STD	0.09	0.06	0.05	0.10	0.09	0.02	0.07
Skewness	2.57	2.54	2.24	2.34	2.51	2.23	2.63
kurtosis	9.26	8.96	7.39	8.00	9.01	7.89	9.94
Auto-Correlation	0.97	0.78	0.96	0.97	0.97	0.95	0.96
1/30/2004 - 12/31/2010							
Mean	0.05	0.03	0.03	0.06	0.05	0.01	0.05
STD	0.10	0.07	0.06	0.11	0.10	0.02	0.08
Skewness	2.29	2.61	2.22	2.15	2.27	2.40	2.31
kurtosis	7.22	8.84	6.65	6.48	7.12	7.67	7.60
Auto-Correlation	0.97	0.84	0.96	0.97	0.97	0.95	0.96

Notes to Table: We report the first four sample moments and the first order autocorrelation of asset-weighted PDs of Banking Groups.

**Table 3: Asset-Weighted PDs and Changes in PD's Rank Correlation
January 30, 2004 to December 31, 2010**

	Asset-Weighted PDs						
	Merton	Merton Garch- MIDAS ST	Merton Garch- MIDAS LT	Geske Total	Geske ST	Geske LT	Heston & Nandi
Merton	<u>1.00</u>	<u>0.69</u>	<u>0.71</u>	<u>0.90</u>	<u>0.97</u>	<u>0.69</u>	<u>0.88</u>
Merton Garch-MIDAS ST	<u>0.69</u>	<u>1.00</u>	<u>0.70</u>	<u>0.67</u>	<u>0.69</u>	<u>0.52</u>	<u>0.68</u>
Merton Garch-MIDAS LT	<u>0.71</u>	<u>0.70</u>	<u>1.00</u>	<u>0.67</u>	<u>0.71</u>	<u>0.53</u>	<u>0.72</u>
Geske Total	<u>0.90</u>	<u>0.67</u>	<u>0.67</u>	<u>1.00</u>	<u>0.90</u>	<u>0.78</u>	<u>0.80</u>
Geske ST	<u>0.97</u>	<u>0.69</u>	<u>0.71</u>	<u>0.90</u>	<u>1.00</u>	<u>0.68</u>	<u>0.87</u>
Geske LT	<u>0.69</u>	<u>0.52</u>	<u>0.53</u>	<u>0.78</u>	<u>0.68</u>	<u>1.00</u>	<u>0.62</u>
Heston & Nandi	<u>0.88</u>	<u>0.68</u>	<u>0.72</u>	<u>0.80</u>	<u>0.87</u>	<u>0.62</u>	<u>1.00</u>
	Asset-Weighted PD Changes						
	Merton	Merton Garch-MIDAS ST	Merton Garch-MIDAS LT	Geske Total	Geske ST	Geske LT	Heston & Nandi
Merton	<u>1.00</u>	<u>0.19</u>	<u>0.35</u>	<u>0.85</u>	<u>0.97</u>	<u>0.42</u>	<u>0.70</u>
Merton Garch-MIDAS ST	<u>0.19</u>	<u>1.00</u>	0.06	<u>0.22</u>	<u>0.19</u>	<u>0.14</u>	<u>0.15</u>
Merton Garch-MIDAS LT	<u>0.35</u>	0.06	<u>1.00</u>	<u>0.35</u>	<u>0.34</u>	<u>0.15</u>	<u>0.31</u>
Geske Total	<u>0.85</u>	<u>0.22</u>	<u>0.35</u>	<u>1.00</u>	<u>0.85</u>	<u>0.56</u>	<u>0.66</u>
Geske ST	<u>0.97</u>	<u>0.19</u>	<u>0.34</u>	<u>0.85</u>	<u>1.00</u>	<u>0.41</u>	<u>0.70</u>
Geske LT	<u>0.42</u>	<u>0.14</u>	<u>0.15</u>	<u>0.56</u>	<u>0.41</u>	<u>1.00</u>	<u>0.34</u>
Heston & Nandi	<u>0.70</u>	<u>0.15</u>	<u>0.31</u>	<u>0.66</u>	<u>0.70</u>	<u>0.34</u>	<u>1.00</u>

Notes to Table: We report Kendall correlation matrix of asset-weighted PDs and PD's changes for banking groups from 2004 to 2010. A bold value with underscore indicates significance at the 95% level, whereas a bold value without underscore indicates significance at the 90% level.

Table 4: Ranking Scores by Granger Causality Test

	Non-Standardized for 17 Banking Groups, May 2001- December 2010			Standardized for 17 Banking Groups, May 2001- December 2010		
	Score	Count	Scores/Counts	Score	Count	Scores/Counts
	s	s		s	s	
Merton	4	136	0.03	4	136	0.03
GARCH_MIDAS ST	39	153	0.25	39	153	0.25
GARCH_MIDAS LT	1	157	0.01	1	157	0.01
HestonNandi	-13	145	-0.09	-13	145	-0.09
Geske All	-4	126	-0.03	-3	127	-0.02
Geske ST	8	134	0.06	9	135	0.07
Geske LT	-35	133	-0.26	-37	135	-0.27
	Non-Standardized for 11 Banking Groups, January 2004- September 2010			Standardized for 11 Banking Groups, January 2004- September 2010		
	Score	Count	Scores/Counts	Score	Count	Scores/Counts
	s	s		s	s	
Merton	-17	95	-0.18	-17	95	-0.18
GARCH_MIDAS ST	30	100	0.30	30	100	0.30
GARCH_MIDAS LT	13	105	0.12	13	105	0.12
HestonNandi	-18	104	-0.17	-19	105	-0.18
Geske All	-10	90	-0.11	-10	90	-0.11
Geske ST	-11	99	-0.11	-11	99	-0.11
Geske LT	-37	93	-0.40	-36	94	-0.38
CDS	50	88	0.57	50	88	0.57

Notes to Table: This table contains the ranking scores according to Granger Causality test. To rank the measures, we give a measure +1 if it Granger causes another measure at 1% of confidence level and -1 if it is Granger caused by another measure. The standardized measures are constructed with mean 0 and standard deviation 1.

Table 5: Ranking Scores by Price Discovery Test

	Non-Standardized for 17 Banking Groups, May 2001- December 2010			Standardized for 17 Banking Groups, May 2001- December 2010		
	Score	Count	Scores/Counts	Score	Count	Scores/Counts
	s	s		s	s	
Merton	6	102	0.06	8	102	0.08
GARCH_MIDAS ST	-56	102	-0.55	-72	102	-0.71
GARCH_MIDAS LT	64	102	0.63	20	102	0.20
HestonNandi	-20	102	-0.20	-32	102	-0.31
Geske All	-15	101	-0.15	33	101	0.33
Geske ST	12	100	0.12	40	100	0.40
Geske LT	9	101	0.09	3	101	0.03

	Non-Standardized for 11 Banking Groups, January 2004- September 2010			Standardized for 11 Banking Groups, January 2004- September 2010		
	Score	Count	Scores/Counts	Score	Count	Scores/Counts
	s	s		s	s	
Merton	17	77	0.22	7	77	0.09
GARCH_MIDAS ST	-35	77	-0.45	-45	77	-0.58
GARCH_MIDAS LT	53	77	0.69	11	77	0.14
HestonNandi	17	77	0.22	13	77	0.17
Geske All	-14	76	-0.18	11	77	0.14
Geske ST	-6	76	-0.08	-13	77	-0.17
Geske LT	44	76	0.58	32	76	0.42
CDS Premium	-76	76	-1.00	-16	76	-0.21

Notes to Table: This table reports the market contribution to the price discovery by means of Gonzalo and Granger permanent-transitory (PT) component decomposition. To rank the measures, we give a score of +1 if the measure gets values larger than 0.5 in the corresponding price discovery metric and -1 if it gets values lower than 0.5. The standardized measures are constructed with mean 0 and standard deviation 1.

Table 6: Ranking Scores by McFadden R-squared, 2007-2009

	Non-Standardized for 17 Banking Groups			Standardized for 17 Banking Groups		
	Score	Count	Scores/Counts	Score	Count	Scores/Counts
	s	s		s	s	
Merton	-6	86	-0.07	-7	85	-0.08
GARCH_MIDAS ST	-13	81	-0.16	-12	80	-0.15
GARCH_MIDAS LT	39	85	0.46	43	79	0.54
HestonNandi	-10	86	-0.12	-11	85	-0.13
Geske All	13	89	0.15	12	88	0.14
Geske ST	-39	85	-0.46	-40	84	-0.48
Geske LT	16	60	0.27	15	59	0.25
	Non-Standardized for 11 Banking Groups			Standardized for 11 Banking Groups		
	Score	Count	Scores/Counts	Score	Count	Scores/Counts
	s	s		s	s	
Merton	-3	71	-0.04	-4	70	-0.06
GARCH_MIDAS ST	-13	65	-0.20	-12	64	-0.19
GARCH_MIDAS LT	21	71	0.30	24	64	0.38
HestonNandi	3	71	0.04	2	70	0.03
Geske All	8	70	0.11	7	69	0.10
Geske ST	-32	70	-0.46	-33	69	-0.48
Geske LT	11	41	0.27	10	40	0.25
CDS Premium	5	71	0.07	6	70	0.09

Notes to Table: This table contains the ranking scores according to McFadden R-squared. To rank the measures, we compare the McFadden R-squared by pairs and assign a score of +1 to the measure with the highest R-squared and -1 to the one with the lowest R-squared. The multinomial logit regressions have the independent variable with lags up to 3. The standardized measures are constructed with mean 0 and standard deviation 1.