3. ESTIMATING PROBABILITY OF DEFAULT FOR SYSTEMICALLY IMPORTANT FINANCIAL INSTITUTIONS DURING COVID-19 PANDEMIC. EVIDENCE FROM EUROPE AND USA

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Abstract

In this paper, we estimate the probability of default for 30 systemically important financial institutions from Europe and USA over seventeen years, from 2004 to 2020. The results indicate that the default risk has increased during the COVID-19 pandemic, but is significantly lower as compared to the period preceding the financial crisis of 2008. Moreover, the American banks appear to absorb the shock caused by COVID-19 much more smoothly as compared to their European peers.

Keywords: KMV model; COVID-19 pandemic; systemic risk

JEL Classification: C6, E5, H1, I15

1. Introduction

The Great Recession underlined the need for comprehensive analysis of systemic risk. Aside from identifying causes that may lead to a systemic crisis in a financial system, identifying possible financial institutions that may play a crucial role in the start of a crisis is an essential endeavor. Furthermore, it is critical to have instruments to analyze the state of the financial system at any given time in order to understand if it is on the verge of a crisis or not. Systemic

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crises generally start with a single or small group of financial institutions and spread to the rest of the financial system, eventually impacting the real economy. In addition to monitoring individual financial institutions, it is vital to identify contagion mechanisms and define strategies to limit the consequences of systemic breakdowns. The potential way the financial institutions relate to each other in a network is crucial to the contagion process that was discussed in the literature (Boss *et al*., 2004; Furfine, 2003; Inaoka *et al*., 2004; and Soramaki *et al*., 2007).

The COVID-19 pandemic has caused huge damages to economies and financial institutions around the world, and many individuals and firms faced serious disruptions in their income. To diminish the economic losses of the health crisis, the governments around the world initiated a series of stimulus measures, such as VAT reduction, grants for small and medium-sized enterprises, or moratoriums on debt repayments. The last one was devoted to ease the loan terms for impacted customers and, in most of the countries, it involved the full postponement of payments for a period between 6 and 9 months. However, these moratoriums might have a significant impact on the balance sheets since the restructured loans could become nonperforming, which would require additional provisioning.

Until nowadays, the literature investigating the impact of COVID-19 pandemic was mainly focused on stock volatility and negative returns (Al-Awadhi *et al*., 2020; Baker *et al*., 2020; Cepoi, 2020; Corbet *et al*., 2020; Zhang *et al*., 2020), cryptocurrencies behavior (Conlon and McGee, 2020; Goodell and Goutte, 2020; Iqbal *et al*., 2020; Mariana *et al*., 2020) or across oil and gold markets (Akhtaruzzaman *et al*., 2020; Mensi *et al*., 2020; Sharif *et al*., 2020). However, there are only a few studies investigating to which extent the COVID-19 pandemics affected the financial system's stability. According to Acharya and Steffen (2020), "firms in industries such as retail, hotel and travel have experienced an immediate drop in cash flows and thus have an unusual high demand for liquidity during the economic shutdown. However, other firms also appear to be scrambling for liquidity because of the high uncertainty as to when and how much economic activity could recover". Given this reality, economic agents as well as the governments expected that the financial sector, especially banks, would play a crucial role in COVID-19 shock absorption, by providing the much-needed funding (Demirguc-Kunt et al., 2020). Moreover, Schularick *et al*. (2020) argued that due to COVID-19 shock the European banks could experience losses around 600 billion euros in a severe scenario and proposed a precautionary recapitalization.

In this paper, we provide fresh and novel evidence of the probability of default for systemically important financial institutions from Europe and USA during the COVID-19 pandemic. By employing the Moody's KMV model we reveal that default risk associated with the pandemic is significantly lower as compared to the period preceding the financial crisis of 2008. Furthermore, the American financial system appears to absorb the shock caused by COVID-19 much smoother.

The remainder of the paper is organized as follows. Section 2 presents the related literature; Section 3 describes the KMV model; Section 4 discusses the data and the results, while Section 5 concludes the paper.

2. Literature Review

The probability of default of a financial institution is defined as the possibility that unanticipated losses generated by the portfolio of debtors exceed bank capital based on the balance sheet data. Accounting and market information has been used in the literature to focus on assessing bank credit risk and on determining the probability of default. Accounting-based studies have used mostly two proxies for bank risk: the NPL ratio and the Z-score. Because it reflects the quality of a loan portfolio, the NPL ratio (nonperforming loans to total loans) or variations in the ratio were employed as a measure of a bank's strength (Baselga *et al*., 2015). A higher value of this ratio suggests a greater likelihood of the bank defaulting. Similarly, the Z-score is commonly used to assess bank risk (Lepetit and Strobel, 2015). A higher Z-score suggests that a bank is less likely to fail (Delis and Staikouras, 2011).

Similarly, research relying on market information as a supplement to accounting indications has been built on the Merton (1974) method to model credit default risk. Credit risk spread (Drago *et al*., 2017) or credit ratings (Wang, 2017) have also been utilized in several studies. De Lisa *et al*. (2011) developed a model to assess the chance of default for financial institutions based on the Basel accords of capital requirements for credit risk.

Bank risk was historically assessed using indicators linked with several risk categories, such as capital adequacy, asset quality, liquidity, and business model and management. In addition, the European Bank Authority (2015) established a set of measures to evaluate bank risk profiles which also managed to demonstrate the predicted connections between indicators and bank risk.

One of the most well-known base measurements is the distance to default; this metric is based on Merton (1974), which has been further developed by the KMV Corporation. It represents the valuation of the equity as a European call option. According to Merton, the strike price of the option is equal to the market value of the debt. The company will fail only when its assessment falls below the face value estimation of the obligation (Kollar & Cisko 2014).

The probability of default calculates the rate or chance that the value of the firms' assets falls below the market value of debt. According to Bohn (2000), the KMV model obtains all the data in accounting factors and the standard agency rating.

Farmen *et al*. (2004) used the actual probability measure to explore the default probability and promote the use of the Black-Scholes-Merton (1973) system for risk management reasons and provided a hypothetical basis for experimental analyses of default likelihood (Farmen *et al*. 2004). Bharath and Shumway (2008) used the Merton models to calculate the default risk for public companies listed on the US stock exchange.

Until now, only few studies have investigated the impact of the COVID-19 pandemic on banking stability, and none provided a clear picture of the potential risks associated with pandemic support measures. Kasinger *et al*. (2021) investigate loans under moratoriums for several European countries in the second quarter of 2020 and elaborate potential scenarios for the future level of NPLs, assuming that a percentage between 0 and 50% of the affected loans will become non-performing. Thus, if 25% of all loans under the moratorium become non-performing, aggregate non-performing loans (NPLs) would increase by approximately EUR 216 billion. In addition, Ari *et al*. (2021) forecast the level of NPLs during bank crisis episodes based on bank- and country-specific variables. According to them, "European crisis countries entered the COVID-19 pandemic with substantially higher government debt and lower bank profitability than before the GFC. Based on our analysis, these factors induce worse outcomes for NPL". '

Žunić *et al*. (2021) and Foglia (2022) argued that the COVID-19 pandemic induced a delayed effect on NPLs due to the application of the moratorium on loans in the European countries. Government support measures have essentially 'frozen' bank portfolios in many countries. Finally, Park and Shin (2021) argued that as corporate losses due to pandemics increase, the default risk would materialize, and consequently the NPL rate would rise.

This study is based on the KMV model (2002), which was adaptated based on the Black and Scholes model (Black and Scholes, 1973) and the Merton model (Merton, 1974).

3. Methodology

One of the practical implementations of the Merton (1974) model is the KMV approach, successfully developed and marketed by the KMV Corporation, until it was acquired by Moody's in April 2002. Until now, the literature investigating the default probabilities of financial institutions has gained steam (Wang *et al*., 2020; Donker *et al*., 2020; Fiordelisi and Marqués-Ibañez, 2013; Fiordelisi *et al*., 2011). In addition, there is evidence from comparative studies that the default probabilities estimation in the KMV model offers better accuracy than agency credit ratings for global financial firms (Câmara *et al*., 2012).

Starting from origins, the Merton (1974) model uses market capitalization of the firm, the face value of debt, and the volatility of the stock returns for the respective firm in order to quantify the default probabilities. The model assumes that the company issued a zero-coupon bond and it is supposed to go bankrupt when the debt reaches maturity (moment $\boldsymbol{T}$) and the market value of the assets ($\boldsymbol{V}$) goes below the debt that needs to be reimbursed ($\boldsymbol{F}$). In the other scenario, the company pays the debt in full and the difference is represented by the firm's capital, which can be expressed similar to the payoff of a European CALL option:

$$E_T = max(V_T - F) \tag{1}$$

The KMV model assumes that the firm's assets follow a geometric Brownian motion, such as:

$$dV_t = \mu_V V_t dt + \sigma_V V_t dB_t \tag{2}$$

where: $\boldsymbol{\mu_V}$ is the expected continuously compounded return of the firm market value of assets ($\boldsymbol{V_t}$), $\boldsymbol{\sigma_V}$ is the volatility of firm returns and $\boldsymbol{dB_t}$ is a standard Wiener process.

The model applies the Black and Scholes (1973) formula to compute the value of the firm's capital by calculating the price of a Call option on the assets of the firm ($\boldsymbol{V_t}$) and using as strike "price" the face value of the debt ($\boldsymbol{F}$) at the maturity $\boldsymbol{T}$.

$$E_t = N(d_1)V_t - Fe^{-r(T-t)}N(d_2) \tag{3}$$

In Eq. (3), $\boldsymbol{E_t}$ is the market value of the firm's equity, $\boldsymbol{r}$ is the instantaneous risk-free rate, $\boldsymbol{F}$ is the face value of the firm's debt and $\boldsymbol{N}(\cdot)$ is the cumulative normal distribution function with d_1 and d_2 calculated as:

$$d_1 = \frac{ln\frac{V_t}{F} + (r + 0.5\sigma_V^2)(T-t)}{\sigma_V\sqrt{T-t}}, \qquad d_2 = d_1 - \sigma_V\sqrt{T-t} \tag{4}$$

Using Ito's lemma, the observable equity volatility can be expressed as a function of the unobservable term which is the volatility of the firm's assets:

$$\sigma_E = \frac{V_t}{E_t} N(d_1)\sigma_V \tag{5}$$

The default probability is then defined by the execution probability of a European Put option having as support the market value of the firm's assets and as strike the face value of the firm's debt.

The formula for the option price can be written as follows:

$$P_t = Fe^{-r(T-t)}N(-d_2) - V_tN(-d_1) \tag{6}$$

Therefore, the default probability of the firm is denoted by the following:

$$PD = N(-d_2) \tag{7}$$

The practical implementation of the KMV model proposes a few improvements. First, the strike is replaced by DP (default point), which is calculated as follows:

$$DP = STD + 0.5LTD \tag{8}$$

In Eq. (8), STD represents the short-term debt and LTD is the long-term debt. Both measures are extracted from the quarterly balance sheet.

On top, the risk-free rate $(\boldsymbol{r})$ is replaced by the drift term $(\boldsymbol{\mu_V})$. The drift term is computed by using the CAPM model in order to obtain the expected returns for each financial institution. Finally, the distance to default (DD) is summarized in Eq. (9):

$$DD = \frac{\ln\left(\frac{V_t}{DP}\right) + (\mu_V - 0.5\sigma_V^2)(T-t)}{\sigma_V\sqrt{T-t}} \tag{9}$$

As a result, the default probability (PD) will be now denoted by the expected default frequency (EDF), and is calculated as follows:

$$EDF = N(-DD) \tag{10}$$

We use the KMV model to compute the Estimated Default Frequencies for the 30 largest financial institution from Europe and United States during The Great Recession, The Sovereign Debt Crisis and the COVID-19 Pandemic. For data processing and computing purposes, we use Matlab. The code used to estimate the results of this paper is represented by the personal processing of the authors.

4. Data and Results

We used quarterly aggregated data from Refinitiv to estimate all the variables from the model. The description of each variable can be found in Table 1.

Table 2 provides the average estimated default frequency during each major crisis in the last seventeen years. By looking at the ADF (Aggregated Default Frequency) for each financial institution over such a broad time horizon it makes possible a clear comparison between the past and present major shocks.

Table 1

KMV Variables

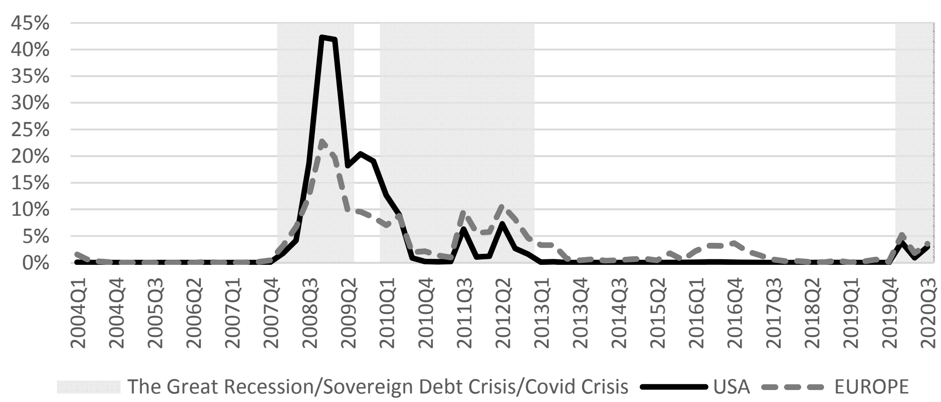
Variables	Description and source
Market Value of Equity (E)	Denoted by the daily observations on market capitalization. Data Source: Refinitiv
Volatility of the firm's assets (σ_V)	Following Vassalou and Xing (2004) we employ an iterative procedure using the past 12 months daily data to obtain the volatility of equity (σ_E) . The equity volatility is then used as an initial value for the estimation of σ_V by solving the system created with equations (3) and (5). Data Source: Refinitiv
Market Value of Assets (V)	Using the Black-Scholes (1973) formula for each trading day of the past 12 months, we compute V using E as the market value of equity of that day by solving the equation system using formulas (3) and (5).

Face Value of Debt (L)	Face Value of Debt extracted from the Quarterly Balance Sheet. Data Source: Refinitiv
Default Point (DP)	Calculated as DP = STD + 0.5LTD. Using the Face Value of the Long-Term and Short-Term Debt from the Quarterly Balance Sheet. Data Source: Refinitiv
Risk Free Rate (r)	Monthly data for the 1-year Yield of United States Treasury Bill for the United States. Data Source: Refinitiv; and monthly data for the 1-year Yield of the Euro Area. Data Source: European Central Bank
Expected return of the firm's assets (μ_V)	Calculated using daily frequency observations for the CAPM Model: $\mu_V = E[Ri] = r + \beta(E[R_m] - r)$. The return of the S&P 500 Index has been used as market benchmark (for US) and Euro Stoxx 50 (for Europe) to calculate the expected market return $(E[R_m])$ and the risk indicator (β). Data Source: Refinitiv

According to the estimated results, several findings come to light. First, in Figure 1 one may see that The Great Recession had the most powerful impact on the overall financial system, while systemically important financial institutions from the United States were much more impacted than the European financial system in the past. However, despite this severe reaction during the Great Recession, the US financial system exhibited more resilience during the current COVID-19 crisis and also during the Sovereign Debt Crisis.

Figure 1

Aggregated Default Frequency



Source: Authors' personal processing.

In Table 2 one can find the average Estimated Default Frequency computed with the KMV model for each financial institution and separated by region in each crisis period. There are three time horizons: The Great Recession (2008Q1 – 2009Q1), The Sovereign Debt Crisis (2010Q1 – 2012Q3) and the COVID-19 Pandemic (2020Q1-2020Q4).

Even though this paper illustrates a stable outlook for the financial system, the balance sheets of the systemically important financial institutions will require special attention from regulators once we see the impact of debt moratoriums, since the restructured loans can become non-performing and this has the potential to create the need for additional provisioning. The results of the KMV model are presented in Figure 1. We use the Estimated Default Frequency (EDF) computed with the KMV model and define the Aggregated Default Frequency (ADF) as the EDF weighted average by assets value for the financial institutions separated by region:

$$ADF = \sum_{i=1}^{n} \frac{ASSETS_i}{TOTAL\ ASSETS} EDF_i \qquad (11)$$

Table 2

Average Estimated Default Frequency during each Crisis Period

Region	Financial Institution	The Great Recession	Sovereign debt crisis	Covid-19 Pandemic
USA	Wells Fargo & Company	11%	1%	1%
	JPMorgan Chase & CO	25%	3%	2%
	Bank of America Corp	29%	8%	4%
	State Street Corp	15%	1%	1%
	Morgan Stanley	25%	2%	2%
	Goldman Sachs Group Inc	10%	0%	3%
	Bank of New York Mellon	13%	1%	1%
	American International Group	31%	6%	2%
	Citigroup Inc	32%	6%	8%
	Royal Bank of Canada	7%	0%	1%
	US Bancorp	4%	0%	1%
	Toronto Dominion Bank	0%	0%	0%
	MTB	1%	0%	0%
	PNC	5%	0%	0%
	FITB	20%	3%	3%
	Total USA	**21%**	**4%**	**3%**
EUROPE	HSBC Holdings PLC	0%	0%	0%
	UBS Group AG	42%	10%	3%
	BNP Paribas SA	2%	3%	8%
	Intesa Sanpaolo SpA	3%	5%	1%
	Banco Santander	2%	0%	0%
	Deutsche Bank AG NA	45%	20%	14%
	BBVA	1%	0%	1%
	UniCredit SpA	6%	4%	0%
	Societe Generale SA	21%	15%	12%
	NatWest Group PLC	0%	2%	0%
	Lloyds Bank	0%	0%	0%
	Barclays PLC	4%	0%	0%
	Nordea Bank Abp	0%	0%	0%
	ING Groep NV	18%	12%	1%
	Credit Suisse Group AG	20%	6%	2%
	Total Europe	**12%**	**6%**	**4%**

5. Conclusions

This study offers empirical evidence on the impact of the COVID-19 pandemic on the financial system. By employing Moody's KMV model, we show that the financial system was far more resilient during the COVID-19 pandemic as compared to The Great Recession and the Sovereign Debt Crisis. In addition, the US financial system shows more resilience versus Europe today, especially due to moratoriums on debt repayments. Even though the results indicate that is unlikely to have a banking crisis caused by the COVID-19 pandemic, a great deal of uncertainty still remains related to the suspended loans associated with moratoriums that might have a negative impact on financial stability in 2022, as both the higher interest rates and inflationary pressures place the consumers purchasing power in a stressful position that can seriously affect the global financial stability.

These findings should be interpreted with caution, since one major limitation of the current study is that the model used in this paper represents mostly the base of the option pricing models, so they are currently only at a theoretical stage, with further development required for practical application. However, this can represent an opportunity for future research in the field, as these results can be used in future studies to assess the potential contagion effects between systemically important financial institutions.

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