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The papers that are presented to our magazine for publication are submitted anonymously to a double level of peer review.

The first level is a review of eligibility, implemented on the paper by the members of the Editorial Board, who assess the adequacy of the paper to the typical topics of the magazine.

The second level is a review of suitability for publication, implemented on the paper by two referees, selected within the Editorial Board, the Scientific Committee or externally among academics, scholars, experts on the subject who assess the content and the form.

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"Risk Management Magazine" is the AIFIRM (Italian Association of Financial Industry Risk Managers) magazine, fully dedicated to risk management topics.

The organization includes the managing editor, a joint manager and an Editorial Board and a Scientific Committee composed by academics.

The magazine promotes the diffusion of all content related to risk management topics, from regulatory aspects, to organizational and technical issues and all articles will be examined with interest through the Scientific Council.

The papers shall be presented in Microsoft Word format, font Times New Roman 10 and shall have between 5.000 and 12.000 words; tables and graphs are welcome.

The bibliography shall be written in APA format and shall accuratel specify the sources.

An Abstract in English is required (less than 200 words) highlighting the Key words.

The authors bear sole responsibility for the opinions expressed in the articles.

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La bibliografia deve essere redatta in formato APA, specificando accuratamente le fonti.

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Managing the Risks of Negative Interest Rates

Ioannis Akkizidis (Wolters Kluwer)

Abstract

The acceleration in the issuance of government debt since the global financial crisis has led central bankers to engineer interest rates that are historically low in nominal terms and consistently lower than inflation rates. Although the ostensible aim of this policy is to stimulate economic growth, maintaining negative real rates also goes a long way so that government debt is manageable and will decline in the long run, relative to the size of the economy.

Financial institutions hold the great majority of government debt, and their books of retail and corporate loans are expanding briskly at a time when ultra-low interest rates make borrowing especially attractive. Rates paid on deposits are low, in advanced economies, even negative in the euro zone in nominal terms. That helps to offset the reduction in income that banks earn on their lending. Even so, the extreme and unique conditions resulting from persistent negative real interest rates mean that banks must take particular care to manage their interest-rate risk in the context of other risk types and the banks' profit-and-loss analysis.

1. The course of interest rates

There are three key measures to observe when considering the evolution of interest rates: 1. The Consumer Price Index (CPI), which reflects inflation in a given economy; 2. the average money-market rate, which reflects the interbank rate; and 3. the real money-market rate, which is the second figure minus the first.

As illustrated in **Figure 1**, since 2007, when the financial crisis began, nominal money-market rates, in Italy and the euro zone more broadly, have significantly deteriorated, turning negative in the last six years. The CPI has experienced more muted declines, punctuated by intermittent spikes, including during the last year. Until the financial crisis, money-market rates closely tracked the CPI. The decoupling since the crisis has left real money-market rates significantly negative. These negative real rates have made borrowing more appealing, but lenders are having to cope with thinner interest margins.

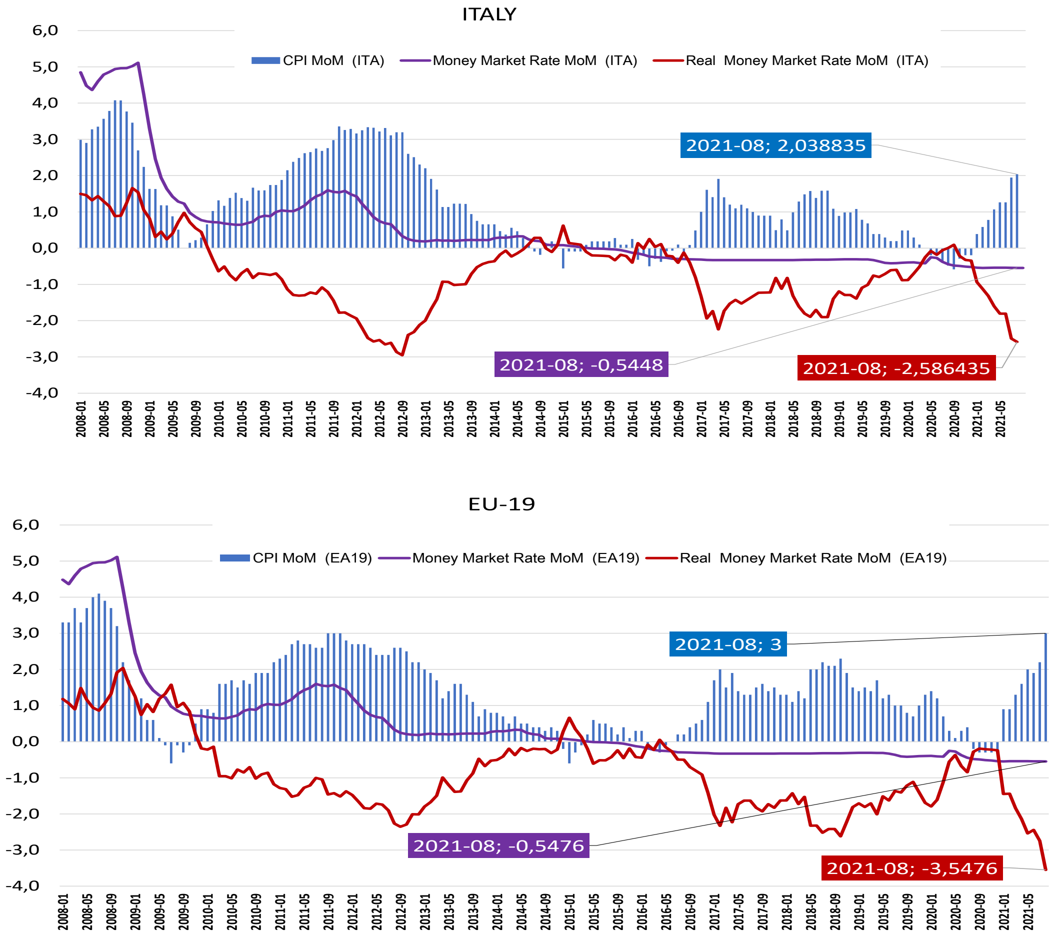

Figure 1: Consumer Price Index (CPI), nominal and real money-market rates in Italy and the euro zone

2. The ratios of government and corporate debt to GDP

Government and corporate debt as a share of gross domestic product has expanded since 2008, as illustrated in **Figure 2**, albeit to different degrees. The ratio of government debt to GDP exceeds 100% in advanced economies, and barely half that level in developing economies. Banks and insurance companies hold a significant amount of negative- or low-positive-yielding government bonds issued in advanced economies. Although those bonds are of high quality and are highly liquid, they are not profitable at all.

Corporate debt in advanced economies has held fairly steady, just below 100% of GDP. Corporate debt issued in emerging economies has grown from 60% of GDP to almost 110%. During the last decade, financial institutions have been supplying credit to corporate customers in both local and global markets. European banks have lent several trillion Euros to borrowers in emerging markets, putting them at greater risk if financial market turmoil in countries such as Turkey, Brazil, India and South Africa intensifies.

For instance, UniCredit, Italy's biggest bank, and other lenders are highly exposed to Turkish banks, whose credit quality is in question, heightening the risk the lenders have taken on. Businesses operating in developing countries generally may face challenges fulfilling credit obligations due to foreign-exchange risk and economic risk resulting from crises such as the Covid-19 pandemic. The fact that businesses in developing economies have invested much of the money they have borrowed in mergers and acquisitions instead of research and development also adds concentration risk and systemic risk.

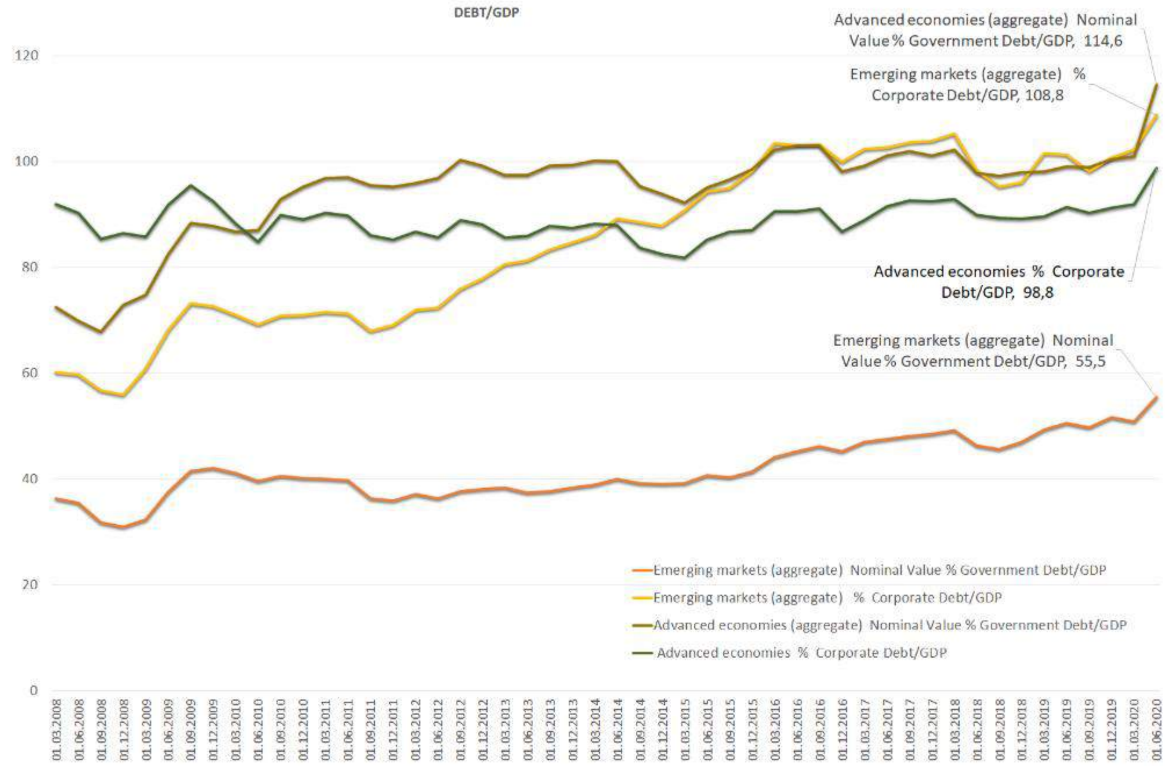

Figure 2: Government and corporate debt-to-GDP ratios in advanced and emerging economies

3. Household loans

Loan interest rates have fallen substantially in the last decade. As shown in **Figure 3**, a typical medium- to long-term mortgage in Italy and the euro zone in general carried a rate of 4% to 6% between 2001 and 2008. Rates today average about 1.3%.

Such dramatically lower rates have brought in significantly more borrowers, raising banks' exposure to retail mortgage portfolios. **Figure 4** shows that euro zone banks' exposure to home loans has soared from about 1.8 trillion euros in 2001 to almost 3.5 trillion euros in 2007 and close to 5 trillion euros today.

The same graph illustrates that home loans consistently have accounted for a majority of banks' credit exposure – 78% at the latest reading – creating concentration risk from mortgages and therefore the housing market.

The availability of low-rate loans, moreover, might be expected to stimulate demand for housing, raising prices, increasing loan demand further, and stretching lenders' exposure even more.

Indeed, after remaining stable between 2009 and 2015, home prices across Europe rose more than 20% over the next five years, as shown in **Figure 5**, although prices in Italy have been flat.

While banks might benefit from the increase in mortgage loan volume and the credit spreads of those portfolios, it is not enough to compensate for the steep decline in interest income.

More important, any spike in interest rates may increase the probability of default on some of those loans.

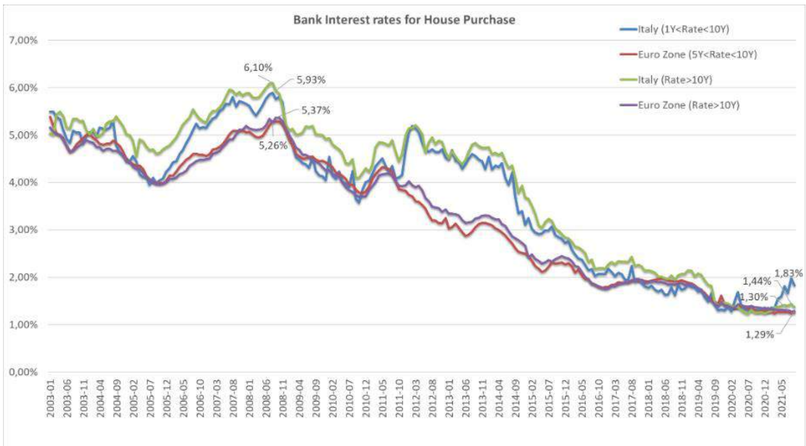

Figure 3: Bank interest rates for home purchase loans in Italy and the euro zone (Source: euro-area-statistics.org)

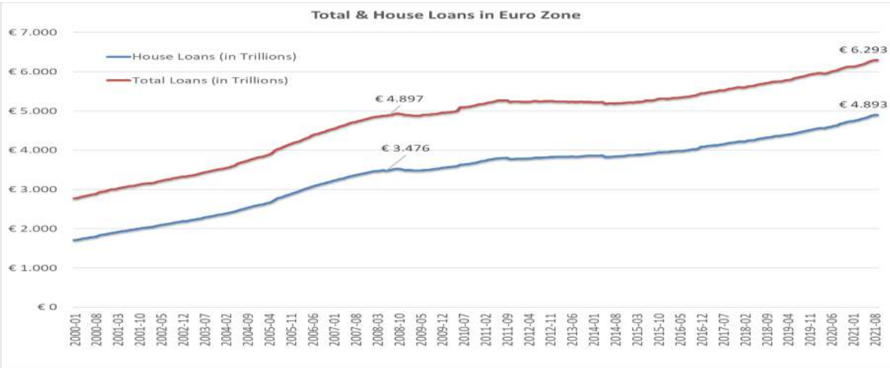

Figure 4: Total value of mortgages and all loans in the euro zone (Source: euro-area-statistics.org)

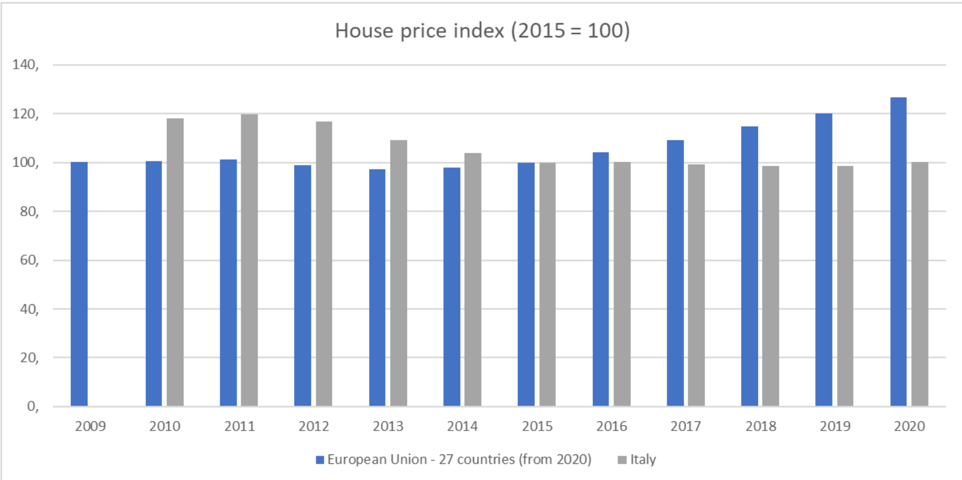

Figure 5: EU House Price Index (Source: Eurostat)

4. Trillions in exposure to household deposits

Interest rates on household deposits have been negligible, reaching almost 0% in the last few years, and real returns have been negative, giving depositors substantial inflation-adjusted losses, making also one of the least attractive investments.

Even so, the volume of deposits has grown at an accelerating pace, although some of the increase lately must be a byproduct of the massive government payments issued in many jurisdictions to blunt the impact of economic shutdowns related to the pandemic.

As shown in **Figure 6**, since 2007, household deposit accounts have risen from 5 trillion euros to 8.6 trillion euros in the euro zone and \$5.9 trillion to \$12.4 trillion in the United States.

Given the extremely low money-market rates illustrated in Figure 1, the banks' depositors must have substantial losses on the household deposit accounts, making them one of the least attractive investments

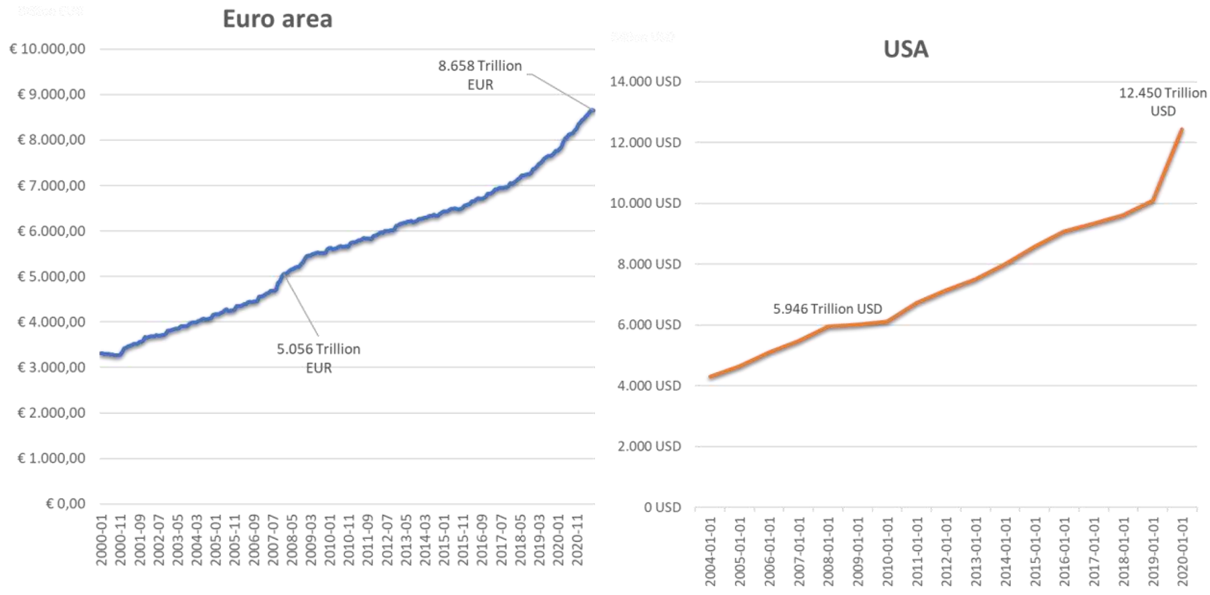

Figure 6: Household deposits in the euro zone and the United States (Source: euro-area-statistics.org)

5. Risk management in an ultra-low-rate world

Credit institutions and financial markets face almost unprecedented challenges from low and negative interest rates. To handle them effectively, banks should define scenarios to identify and measure their impact should the present rate environment persist, and if rates were to rise significantly, either steadily or in spikes, with real rates turning positive. A holistic approach should be taken, in which interest-rate risk is assessed not just on its own but in the context of correlated risks, such as credit, counterparty and behavioral. All strategies involving current and new business must consider interest-rate scenarios that are likely to affect the profit-and-loss statement. **Figure 7** illustrates various developments and circumstances that financial institutions might consider in analyzing interest rates.

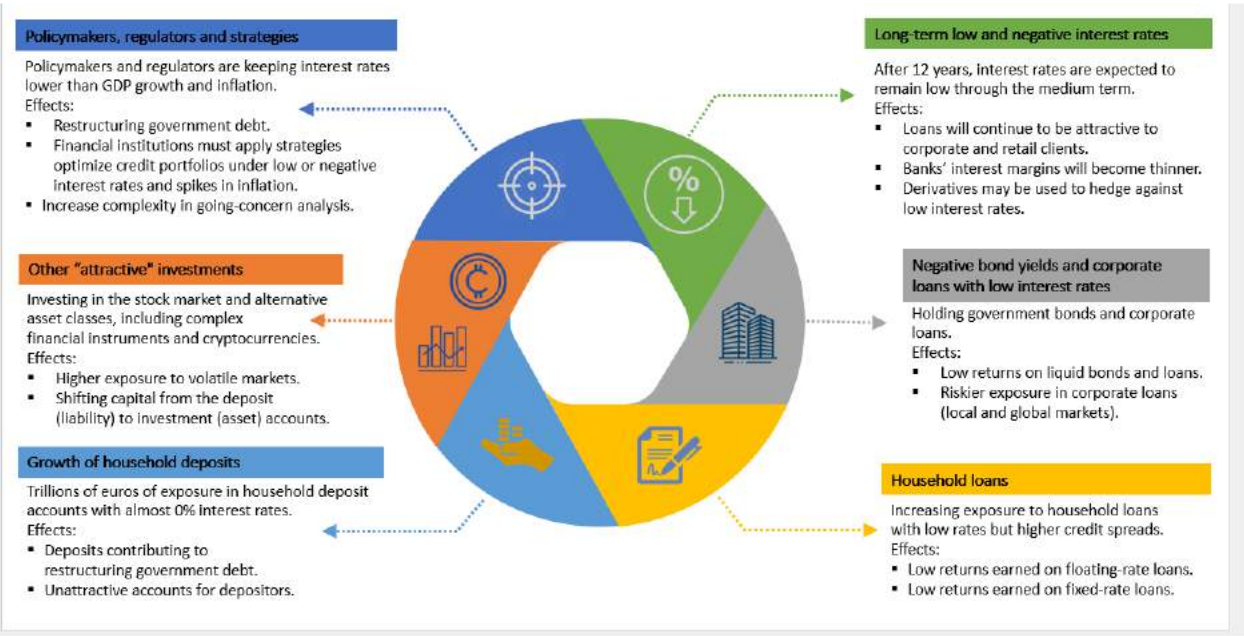

Figure 7: Elements for analyzing risk in a low-interest-rate environment

Here are some specific hypothetical scenarios that highlight the many complexities – and risks – that financial institutions must confront while operating amid persistent, extremely low interest rates:

Scenario A: Real interest rates are kept low to restructure government, corporate and retail debts

Policymakers and regulators in advanced economies maintain interest rates lower than the rates of GDP growth and inflation. As a result, financial institutions holding government and corporate bonds, retail loans, and household deposit accounts contribute to restructuring government and other long-term debt.

Banks increase exposures in liquid, highly rated bonds and loan portfolios, but given the negative or negligible nominal interest rates, they produce negative income. Moreover, stress arises from a reduction in deposits due to withdrawals and the comparative appeal of the stock market or other alternative asset classes, including complex financial instruments, peer-to-peer loans or cryptocurrencies.

Scenario B: Inflation rises, as do interest rates on deposits and retail and corporate loans, but rates on government debt remain low or negative

Consumer prices are rising, but not due to economic growth, and interest rates on government and corporate debt remain low to negative. Banks may define scenarios stressing macroeconomic factors such as inflation rates and stock, house and commodity prices. The increase in house prices reduces the net exposures of mortgage portfolios. There is pressure to raise interest rates on deposits to limit withdrawals. Banks may stress the behavioral risk related to depositor withdrawals due to low interest rates, but banks should also apply strategies to develop new products to win back these depositors. Similarly, interest rates on retail and corporate loans may increase to balance the rise in deposit rates, but higher loan rates may increase the default probability of existing floating-rate loans, and fixed-rate loans may result in high losses. Banks should adjust their strategy on new loans based on higher interest rates, resulting in higher interest income.

Scenario C: Interest rates spike

In this scenario, spikes send interest rates from negative to positive and back again. This may occur due to jumps in inflation, as well as decisions by policymakers. Such volatility could increase behavioral risk in asset and liability accounts. Higher rates may lead to rising loan prepayments and greater demand for fixed-interest-rate loans. Declining interest rates may cause the opposite behavior. Banks must apply hedging strategies against interest-rate volatility. Spikes in rates indicate economic instability and low economic growth; banks should adjust the development of new portfolios accordingly.

6. Managing the present and preparing for the future

In conclusion, low and negative interest rates have become the new, and more challenging, normal in the last decade. Movements in interest rates are driven by macroeconomic factors, and they are highly correlated with behavioral, market and credit risks. The exceptional rate environment, which of course could change at any moment, is forcing banks to reassess their business strategies and the composition of their asset and liability portfolios, or at least it should. Banks must evaluate the impact of negative interest rates, and the prospect of rising or volatile rates, as well as the interplay among various sources of risk, in developing stress scenarios and in their strategic decision making.

Fundamental review of the trading book - Stato dell'arte sulle implementazioni dell'Internal Model Approach

Carlo Frazzei (Banca Sella), Davide Segantin, Patrizia Dolci, Alessandro Garufi (Banco BPM), Simone Luca Zavattari, Ilaria Giommaroni (Unicredit), Andrea Rodonò (Deloitte Consulting) [1]

Disclaimer

Il presente articolo è stato consolidato prima della pubblicazione della bozza di CRR 3 del 27 ottobre 2021. Eventuali integrazioni al presente articolo derivanti dalla release normativa verranno recepiti nel Position Paper FRTB che verrà pubblicato nel Q1 2022. Si fa presente che, essendo il presente documento redatto esclusivamente per fini illustrativi ed esemplificativi, non vuole in alcun modo fornire al lettore regole prescrittive su come adeguare la propria operatività al dettame normativo, che va comunque analizzato nel dettaglio e adattato alla propria operatività. Il fine dichiarato dell'articolo è quello di fornire un *overview* di quanto richiesto dalla normativa e di quanto implementato dagli intermediari per rispondere ai nuovi requisiti normativi per il rischio di mercato.

Abstract

In light of the finalization of the new regulatory framework for market with the adoption of the FRTB at EU level through the publication of CRR III, financial institutions are consolidating the implementations aimed to comply with the new regulatory requirements. The main purpose of this article is to analyze how banks are preparing for the go-live of IMA FRTB reporting – expected to be in January 2024 – focusing on the challenges that they are facing especially in terms of model transformations. In particular, an in-depth analysis will be carried out on the main methodological issues of the new regulatory context technicalities, in order to provide guidelines and market best practices on the Internal Model Approach (IMA) topics shared between Front Office, Risk Management as well as Control Structures.

Alla luce del completamento del nuovo framework normativo per il *market risk* con la pubblicazione da parte di EBA di Regulatory Technical Standard (RTS) afferenti al modello interno ed in attesa del recepimento della FRTB a livello comunitario con la pubblicazione della CRR III, le istituzioni finanziarie stanno consolidando le implementazioni volte ad ottemperare ai nuovi obblighi regolamentari. Il principale obiettivo del presente articolo è quello di analizzare come le banche si stanno preparando al go-live del reporting IMA FRTB – atteso verosimilmente per il gennaio 2024 – con un focus sulle sfide che le stesse stanno affrontando, specialmente in termini di trasformazione dei modelli di business. In particolare sarà effettuato un approfondimento sui principali temi metodologici delle technicalities del nuovo contesto normativo, allo scopo di fornire linee guida e *best practice* di mercato su tematiche relative all'Internal Model Approach (IMA) condivise tra Risk Management, Front Office nonché le Strutture di Controllo.

Key Words:

Fundamental Review of the Trading Book (FRTB), CRR II, Basel Committee on Banking Supervision, Market Risk, Modello Interno, Best Practice, IMA, ES, NMRF, RFET, DRC, PLA

1. Premessa

La *Fundamental Review of the Trading Book* (FRTB) nasce con l'intento di rafforzare la regolamentazione, la vigilanza e la gestione dei rischi del settore bancario, nonché accrescere la sensibilità al rischio delle istituzioni finanziarie. In tale ambito, il *Basel Committee on Banking Supervision* (BCBS) ha definito un nuovo *framework* [1] con l'obiettivo di superare le carenze dimostrate dall'attuale normativa per la valutazione dei rischi di mercato nel corso della crisi finanziaria globale del 2007-08.

Negli ultimi anni si sono susseguiti numerosi interventi normativi volti ad attuare una revisione dei modelli di calcolo per il requisito del rischio di mercato. In ambito comunitario l'adozione del nuovo *framework* è stata guidata dall'inclusione all'interno del pacchetto di revisione della *Capital Requirements Regulation* (CRR II) [2], pubblicata nella Gazzetta Ufficiale dell'Unione Europea il 7 giugno 2019, e da una serie di Atti Delegati, *Implementing Technical Standards* (ITS) e *Regulatory Technical Standards* (RTS) volti a completare il quadro normativo disciplinando specifici *topic*.

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[1] Si ringraziano tutti i partecipanti alla Commissione Congiunta AIFIRM-ASSIOM FOREX che con i propri contributi hanno consentito la predisposizione del presente articolo. In particolare:

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Tali interventi normativi hanno determinato l'introduzione di elementi di novità trasversali ai processi *Front-to-Risk*, con notevoli impatti lungo sostanzialmente quattro direttrici:

- *Trading Book e Banking Book Boundary:* è stata sviluppata una definizione oggettiva del confine tra *Trading* e *Banking Book* basando tale impostazione sul concetto di «*trading intent*» e l'utilizzo di «*presumptive list*». Obiettivo primario del *Regulator* è la riduzione della possibilità di arbitraggio regolamentare;
- *Ruolo dei Trading Desk e Internal Risk Transfer:* i *trading desk* acquisiscono un ruolo centrale all'interno del nuovo *framework* per il rischio di mercato. Il Comitato fornisce una specifica definizione normativa basata su dei prerequisiti ben definiti;
- *Revised Standardised Approach:* l'approccio *Standard* è stato completamente rivisitato e reso *risk-sensitive*, in quanto la mancanza di sensibilità rispetto ai fattori di mercato dell'attuale modello standard è stata considerata come un aspetto chiave su cui intervenire;
- *Revised Internal Model-based Approach:* la scarsa capacità dell'attuale requisito di capitale di assorbire le perdite durante la crisi finanziaria ha convinto il Comitato a revisionare profondamente la normativa sull'approccio a modello interno, sia da un punto di vista qualitativo che quantitativo.

Nell'ambito di tale articolata *review* normativa, una tematica di grande rilievo riguarda sicuramente la modifica del modello per il calcolo del requisito secondo approccio *Standard*, che costituisce una soluzione di *fallback* nel caso in cui il modello interno venga considerato inadeguato per alcuni *desk* ed il suo utilizzo venga revocato.
Infatti, a differenza di quanto accade nell'attuale *framework Basel* 2.5 dove il calcolo del requisito e pertanto la validazione all'utilizzo del modello interno avvengono a livello *firm wide*, con l'introduzione dell'FRTB il concetto di *trading desk* assume il ruolo di unità fondamentale per il calcolo del *capital requirement* per i rischi di mercato.
Pertanto, considerando che la possibilità di capitalizzare un *desk* a modello interno è strettamente dipendente dal superamento di test quantitativi (*Validation Test*) effettuati su base trimestrale, l'implementazione di un modello di calcolo del requisito *Standard* sarà obbligatorio per tutte le istituzioni, anche alla luce della nuova formula di aggregazione del requisito, che prevede l'imposizione di un *floor* sulla base del *capital charge* calcolato a *Standard* sull'intero perimetro *in scope* per i rischi di mercato.

2. Il nuovo framework FRTB per i rischi di mercato – Modello Interno

Sebbene la nuova veste di *fallback solution* per il modello *Standard* rappresenti una delle maggiori novità previste dal regolatore in ambito FRTB, innovazioni altrettanto consistenti ed impattanti sul modello di rischio e sulla struttura IT delle istituzioni sono state previste con riferimento al nuovo approccio per il modello interno.
Da un punto di vista metodologico, il nuovo quadro normativo introduce una profonda revisione delle metriche attualmente utilizzate sotto il *framework Basel* 2.5. Infatti, il capitale regolamentare secondo il modello interno (IMA), è calcolato mediante la seguente formula:

$$\mathrm{CC(IMA)} = \max\,\{\mathrm{IMCC}_{\mathrm{t-1}}; m_c^* \cdot \mathrm{IMCC}_{\mathrm{AVG}}\} + \max\{\mathrm{DRC}_{\mathrm{t-1}}; \mathrm{DRC}_{\mathrm{AVG}}\} + \max\,\{\mathrm{SES}_{\mathrm{t-1}}; \mathrm{SES}_{\mathrm{AVG}}\}$$

Il calcolo del *Capital Charge* è pertanto effettuato tramite l'utilizzo di tre distinte metriche di rischio quali:

- *Internal Model Capital Charge (IMCC)*: le attuali metriche di VaR e SVaR al 99% vengono sostituite da una misura di *Expected Shortfall* (*ES*) calcolata considerando un intervallo di confidenza del 97.5% in un periodo stressato, che permette inoltre di tenere in considerazione il diverso rischio di liquidità dei fattori di rischio.
- *Default Risk Charge (DRC)*: da considerare come un'evoluzione dell'attuale *Incremental Risk Charge* (*IRC*), la metrica DRC si prefigge l'obiettivo di catturare il rischio di *default* relativo alle posizioni presenti all'interno del portafoglio di negoziazione. Rispetto alla misura attualmente utilizzata secondo *Basel* 2.5, il DRC prevede l'inclusione delle posizioni *Equity* (*cash* e derivati) all'interno del perimetro *in scope* ed esclude dal calcolo la componente relativa al rischio di migrazione (*downgrading/upgrading*).
- *Stressed Expected Shortfall* (*SES*) per *Non-Modellable Risk Factor (NMRF)*: tale componente rappresenta la maggiore innovazione rispetto all'attuale *framework* normativo per il rischio di mercato e probabilmente la maggiore *challenge implementativa* per le istituzioni che hanno intenzione di utilizzare il modello interno. Considerata da sempre uno dei *key point* maggiormente dibattuto all'interno dell'*Industry*, la metrica SES è nata con l'esigenza di modellizzare quei fattori di rischio che non soddisfano uno specifico *modellability assessment* e perciò non *eligible* ad essere capitalizzati con un modello di *Expected Shortfall* (IMCC).

In aggiunta, il nuovo *framework* di valutazione del rischio di mercato rivede non solo le metodologie di calcolo delle metriche ma anche i criteri di applicazione delle stesse, introducendo i cosiddetti *Validation Tests*. Infatti, l'adozione dell'*Internal Model Approach* (IMA) per il calcolo del requisito di capitale a livello di *trading desk* in ottica *market risk* è soggetta al superamento di alcuni test quantitativi quali:

- *Profit and Loss Attribution Test (PLAT):* ha l'obiettivo di assicurare l'accuratezza del *risk model* nello stimare la P&L giornaliera. Essa si concretizza in due test quantitativi che devono essere svolti trimestralmente, su un intervallo temporale di 250 *business date*:
    - *Correlation test* tra le serie storiche di HPL (*Hypothetical P&L*) e RTPL (*Risk Theoretical P&L*): *Spearman Correlation*
    - *Distribution test* tra distribuzioni HPL (*Hypothetical P&L*) e RTPL (*Risk Theoretical P&L*): *Kolmogorov-Smirnov (KS)*

- *Backtesting:* prevede confronti tra le misure di VaR *daily* al 97.5% e 99% rispetto ad un anno di osservazioni di APL (*Actual P&L*) e HPL (*Hypotetical P&L*), a livello di *desk*.

Infine, con l'obiettivo di individuare un eventuale *add-on* sulla metrica di IMCC (tramite un moltiplicatore da applicarsi alla metrica stessa), viene previsto un *backtesting* a livello *firm wide*.

3. Focus su Non-Modellable Risk Factor

3.1 Implementazione in CRR2 della definizione di Risk Factor e Mapping da Real Price Observations (RPO) a Risk Factors (RF)

La definizione del perimetro dei fattori di rischio da considerare ai fini del computo dei requisiti di capitale IMA risulta essere il punto di partenza per lo sviluppo del modello interno, in particolare ai fini dell'*assessment* relativo alla modellabilità degli stessi (*Risk Factor Eligibility Test - RFET*), che consente di delineare i perimetri di calcolo rispettivamente della metrica IMCC (per i fattori di rischio modellabili) e della metrica SES (per i fattori di rischio non modellabili).
La definizione dei fattori di rischio da considerare nel *framework* è riportata in dettaglio sia all'interno del paragrafo 31.1 del documento BCBS sia nell'ambito della CRR II. Di fatto, la normativa[2] tende ad indicare come *Risk Factor* da includere nel modello interno tutti quelli utilizzati come input nelle funzioni di *pricing* ("*…all risk factors that are used for pricing…*"), specificando che debbano essere inclusi tutti quelli espressamente previsti a livello di *Standardised Approach* ("*…must include all risk factors that are specified in the standardised approach for the corresponding risk class…*").
Nell'ambito del *Risk Factor Eligibility Test* (RFET), l'oggetto dell'*assessment* risulta essere rappresentato dalle *Real Price Observations* (*RPOs*) (o *Verifiable Price*) che sono ricavate dalle *real transactions*/*committed quotes* secondo le regole definite dalla normativa (EBA RTS marzo 2020 Art.2.3).
L'analisi sulle RPOs deve poi essere tradotta in un "conteggio" sui *Risk Factor* (*RF*) sottostanti ai fini della definizione della modellabilità di ciascuno di essi, in quanto questi ultimi sono i *driver* delle metriche di rischio su cui sono calcolati i requisiti di capitale.
Questo "*mapping*" da RPOs a RF, che deve essere adeguatamente documentato da parte delle istituzioni in apposite *policy*, può essere semplice in alcuni casi in cui si configura una relazione "*one-to-one*" tra RPOs e RF ma pone maggiori problematiche nel momento in cui la relazione sottostante è del tipo "*one-to-many*", ossia quando il prezzo di una RPO è funzione di più fattori di rischio.
In particolare, il documento di *Regulatory Technical Standards* pubblicato da EBA a marzo 2020 [3] [3] nonché la CRR II definiscono come requisito fondamentale per il *mapping* da RPOs a RF il tema della rappresentatività ("*…A verifiable price shall be considered <u>representative</u> of a risk factor…"),* definendo le condizioni da rispettare affinchè tale rappresentatività sia garantita come le seguenti:

1) "*…verifiable price is representative only if there is a <u>close relationship</u> between the risk factor and the verifiable price…*";
2) "*…the institution is <u>capable of extracting</u> the value of the risk factor from the value of the verifiable price… in extracting a risk factor from the value of a verifiable price, <u>further inputs</u>, such as the values of other risk factors or input parameters <u>may be used</u> where necessary.. Any input data or risk factor used in that methodology other than that verifiable price shall be based on <u>objective data</u>.*".

Deve pertanto sussistere una stretta relazione tra il fattore di rischio ed il prezzo della RPO utilizzata nell'ambito del *Risk Factor Eligibility Test* (RFET); inoltre una RPO risulta essere rappresentativa di un determinato fattore di rischio nel momento in cui un'istituzione è in grado di estrarre il valore di quest'ultimo dal valore del suddetto *Verifiable Price*. Pertanto, per poter modellizzare un *Risk Factor* è necessario estrarre il suo valore dal prezzo di un generico strumento.
Tali condizioni ("*<u>close relationship</u>*" e "*<u>capable of extracting</u>*") risultano facilmente raggiungibili nei casi di relazione "*one-to-one*", mentre nei casi "*one-to-many*" vi possono essere alcune situazioni che possono lasciare dubbi interpretativi.
Posto infatti che la normativa ammette il conteggio di più RF per una RPO ("*…An institution should be allowed to identify a <u>verifiable price for more than one risk factor</u>. Any verifiable price may be counted as an observation for <u>all of the risk factors for which it is representative</u>"…*), in tali casi occorre tuttavia provare la rappresentatività della RPO per il RF in oggetto e l'oggettività dei dati ("*<u>objective data</u>"*) utilizzati con riferimento agli altri fattori di rischio inclusi nel *pricing* al fine di poter estrarre il valore del RF oggetto di analisi.
La rappresentatività di una RPO nei confronti dei vari RF potrebbe essere "qualitativamente" provata nell'ambito delle regole di *mapping* definite nelle *policy*, in cui ad ogni strumento finanziario (di una RPO) siano associati i fattori di rischio più rappresentativi.
Non evincendosi dalla normativa la necessità di una verifica "quantitativa" circa la rappresentatività, si ritiene che possa essere sufficiente che le istituzioni inseriscano le informazioni circa il *mapping* all'interno delle *policy* aziendali.

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[2] ***BCBS Final Text Gennaio 2019 art. 31.1 e seguenti***. *[…]Risk factors are the market rates and prices that affect the value of the bank's trading positions. […] A bank's market risk capital requirement models should include all risk factors that are used for pricing […]. A bank's market risk capital requirement model must include all risk factors that are specified in the Standardised Approach for the corresponding risk class […].*

[3] ***EBA RTS marzo 2020, art. 3***.

1. *A verifiable price shall be considered representative of a risk factor as of its observation date where both the following conditions are met:*
   a) *there is a close relationship between the risk factor and the verifiable price;*
   b) *the institution has specified a conceptually sound methodology to <u>extract the value of the risk factor from the verifiable price</u>. Any input data or risk factor used in that methodology other than that verifiable price <u>shall be based on objective data</u>.*
2. *Any verifiable price may be counted <u>for all of the risk factors for which it is representative</u> in accordance with paragraph 1.*

A titolo di esempio, nel caso di un'opzione su *single stock equity*, dipendente da vari fattori di rischio (prezzo dell'azione sottostante, volatilità, dividendo e tasso di sconto), occorrerebbe indicare quelli che si ritengono rappresentativi dello strumento (i.e. volatilità, dividendo).
Più controverso invece appare il tema, nell'ambito delle relazioni "*one-to-many*", della "oggettività" dei fattori di rischio "*other*" rispetto a quello oggetto di analisi, richiesta per poter provare la "*capable of extracting*" del valore di quest'ultimo partendo dal prezzo della RPO.
Riprendendo l'esempio soprastante, quindi, conoscendo il prezzo dell'opzione dovrebbe essere possibile, tramite un'operazione di *reverse engineering*, risalire al valore di tutti i fattori di rischio sottostanti, a patto che siano garantite le condizioni di rappresentatività e oggettività dei dati ("*other"*).
A livello di gruppo di lavoro, alla luce del fatto che non sono ancora disponibili linee guida ben definite lato *Regulator*, non risulta momentaneamente possibile definire una *best practice* di *industry*.
Appare tuttavia condivisibile che il requisito di "oggettività" richiesto non sia interpretabile come necessità che i RF "*other*" siano "modellabili" per poter estrarre il valore del RF oggetto di analisi, ma si presume che la richiesta del *Regulator* faccia più riferimento alla *data quality* dei fattori di rischio "*other*" utilizzati nel *pricing*.

3.2 RFET – Proxy Approach per NMRF e possibilità di classificare come NMRF solo le basi NMRF – MRF

La tematica, disciplinata nell'ambito del paragrafo 31.26 par. 7 del testo del BCBS, si riferisce alla possibilità per le istituzioni di utilizzare delle *proxy* nella definizione dei fattori di rischio, qualora non sia possibile associare ad uno strumento il corrispondente fattore specifico.
Il testo chiarisce che è possibile utilizzare in maniera limitata delle *proxy*, coerentemente con le caratteristiche di regione, qualità e tipologia di strumento, a patto che abbiano caratteristiche similari rispetto al fattore di rischio oggetto di *proxy*.
Nel caso sia utilizzata una *proxy*, sono lasciate due possibilità:

- Utilizzare la *proxy* nel calcolo del *Risk Theoretical PL* per l'esercizio di *PL Attribution*;
- Definire come nuovo fattore di rischio la base tra il fattore di rischio "vero" e la *proxy*, e considerarlo all'interno dell'IMA.

Nel primo caso la banca rischia di fallire la prova di PLA, se la *proxy* non è sufficientemente rappresentativa del fattore di rischio "vero".
Nel secondo caso, la base è capitalizzata, o all'interno dell'*Expected Shortfall* se *modellable*, o all'interno dello *Stress Test* se *non-modellable*.
Tale approccio non è stato recepito in maniera esplicita nella normativa europea, in particolare nell'EBA-RTS-2020-03 (*Risk Factor Modellability*). Nel testo lesgislativo proposto, non si fa infatti riferimento esplicito al concetto di *proxy*. Tuttavia nella sezione di "*Background e rationale*" si discute la possibilità di definire un *risk factor* che non passa il test di modellabilità, scomponendolo in due fattori, uno *modellable* ed uno *non-modellable*. Il medesimo concetto è accennato anche nella risposta alla *Question* 8 delle "*Summary of responses to the consultation and EBA's analysis*" del medesimo documento. Possiamo quindi dedurre che tale possibilità, prevista dal testo di Basilea sia inclusa, anche se solo implicitamente, nella normativa europea.
Per quanto riguarda la definizione delle *proxy*, la normativa europea, in particolare le EBA-GL-2021-07 (*Guidelines on criteria for the use of data inputs*), ne esplicita solo alcuni aspetti. In particolare si tratta delle metodologie di interpolazione, estrapolazione e parametrizzazione. Pur essendo molto precise per queste tematiche, le *guidelines* lasciano alcune lacune per discriminare l'accettabilità o meno delle *proxy* scelte.
Presumibilmente, l'intenzione del regolatore è quella di lasciare al vaglio di *Backtesting*, *PL Attribution* e aggravio del capitale l'adeguatezza e opportunità delle *proxy*.
In sostanza, l'utilizzo di una *proxy* non idonea a rappresentare il rischio specifico e generico del fattore di rischio "vero" porterebbe al fallimento dei test o all'aggravio di capitale: ad esempio *add-on* per il *backtesting*, uscita del *desk* dall'IMA o aumento eccessivo della misura di *Stress Test*.
Un chiarimento da parte del *Supervisor* sull'interpretazione normativa sarebbe opportuno.

3.3 Bucketing approach

Secondo la *provision* descritta all'interno del paragrafo 31.16 del documento BCBS ("*Bucketing approach for the RFET*") e ripresa dall'EBA RTS marzo 2020 (Art.2.5), qualora un fattore di rischio sia rappresentato da un punto su una curva o una superficie (i.e. curva dei tassi di interesse, superfici di volatilità *equity*, …), al fine di contare le RPO per il *modellability assessment* dei RF sottostanti, un'istituzione può far riferimento a due opportunità di *bucketing*, con lo scopo di contare tutti i *verifiable price* assegnati ad un *bucket* al fine di valutare se il *bucket* "passa" il *modellability assessment* per gli eventuali fattori di rischio che appartengono al *bucket* stesso:

- "*Own Bucketing Approach*";
- "*Regulatory Bucketing Approach*".

Viene inoltre specificato che nel momento in cui una banca dovesse fare ricorso al "*Own Bucketing Approach*" in ottica RFET, tale approccio dovrà essere necessariamente utilizzato anche nel calcolo delle *Risk Theoretical P&L* in sede di *P&L Attribution* ("*…all risk factors must correspond to the risk factors that are part of the risk-theoretical profit and loss (RTPL) of the bank for the purpose of the profit and loss (P&L) attribution (PLA) test…*").
Nel caso di adozione del "*Regulatory Bucketing Approach*", in cui sono definiti dallo stesso *Regulator* i *bucket standard* per ogni classe di rischio e dimensione delle curve/matrici, non viene invece specificato in maniera puntuale l'obbligo di un legame con il *bucketing* utilizzato nella *P&L Attribution*.

L'interpretazione dell'*industry* con riferimento a tale casistica (adozione del "*Regulatory Bucketing Approach*" per RFET), è pertanto quella che sia possibile utilizzare un livello di granularità diverso tra *modellability assessment* e *P&L Attribution*, ossia adottare "*Regulatory Bucketing Approach*" per il RFET e "*Own Bucketing Approach*" per PLAT.
Poste tali premesse, permane tuttavia un dubbio legato al fatto che non sembrerebbe sussistere una motivazione consistente che possa condurre alla scelta della prima modalità di *bucketing* ("*Own Bucketing Approach*") per il RFET, considerando che tale scelta condurrebbe a svantaggi in ambito *modellability assessment* in quanto la verifica di modellabilità sarebbe effettuata su un perimetro più granulare di fattori di rischio, con conseguente maggiore probabilità di aumentare il perimetro dei fattori di rischio non modellabili.
In sostanza, verrebbe meno il *trade-off* tra *P&L Attribution* e *Modellability Assessment*, che invece si avrebbe in caso di scelta dell'"*Own Bucketing Approach*" per il RFET, comportando svantaggi in termini di RFET stesso ma benefici in termini di PLAT.
Da ultimo si segnala che invece il *Regulator* (EBA RTS dicembre 2020, Art.2.1 "*Methodology for developing extreme scenarios of future shock applicable to non-modellable risk factors*") non ha lasciato dubbi interpretativi in merito al *Bucketing* da utilizzare in ottica SES per i fattori di rischio non modellabili:

"*The Basel standards clarify that the modellability of risk factors belonging to a curve or to a surface is determined using either (i) the own bucketing approach or (ii) the regulatory bucketing approach. Where the institution opts for the regulatory bucketing approach, a bucket may include more than one risk factor; in this case, the institution is allowed to calculate the stress scenario risk measure at the level of the regulatory bucket, meaning that a single extreme scenario of future shock is determined for all the risk factors in the regulatory bucket.*"

In tal caso la scelta del "*Regulatory Bucketing Approach*" per il RFET permette alle istituzioni di calcolare la misura di rischio stressata a livello di *Regulatory Bucket*, determinando un unico scenario di *shock* per tutti i fattori di rischio che ricadono nel corrispondente *Regulatory Bucket*.

3.4 Confronto con attuale Risk Factor Not In Model Engine (RNIME)

Stanti le attuali *provision* normative, vi è sostanziale *consensus* sul fatto che l'attuale *framework* RNIME non sia esplicitamente presente nel contesto FRTB, bensì questo possa essere assimilato a SES e RRAO rispettivamente su IMA e SA.
Un esempio empirico di fattori di rischio per i quali non si dispone di sufficienti dati giornalieri per poterli includere nelle metriche di VaR e ES potrebbe essere rappresentato dai dati di correlazione *equity*/*equity*: un dubbio interpretativo emerso riguarda tuttavia le modalità di gestione di tale tematica all'interno del nuovo *framework* regolamentare, sebbene il SES preveda metodologie ad hoc per fattori di rischio che presentino poche rilevazioni, o addirittura *fallback approach*.
Opinione condivisa dall'*industry* è che l'eventuale assenza di tali fattori di rischio dal *pricing engine* si traduca in una penalizzazione in termini di *P&L Attribution*, tanto maggiore quanto più importante risulta essere il RF assente, con conseguenti svantaggi in termini di *Validation Test* per i *desk* impattati: pertanto, non ci si attende l'applicazione di un ulteriore *add-on*[4] poiché questo implicherebbe un approccio eccessivamente conservativo e tale da rappresentare un disincentivo ad utilizzare il modello interno.
Rimane tuttavia un dubbio con riferimento ai *template* che alcuni esponenti dell'*industry* hanno recentemente ricevuto dal *Regulator*, con riferimento all'*application* per il *reporting* IMA, da effettuarsi entro la fine del 2022 per le *entities* interessate al modello interno. Nell'ambito del "*Self-assessment questionnaire (SAQ)*" è prevista tra i "*Topics to be covered in the FRTB IMA application*" una sezione specifica "*Risks not in the model engines framework*". Tale richiesta potrebbe essere interpretata come una volontà del *Supervisor* di mantenere il *framework* RNIME, sebbene non sia espressamente citato in nessun documento della normativa FRTB.

3.5 Relazioni tra Non-Modellable Risk Factor e Back-testing

Rispetto a tale tematica, è stata individuata un'incoerenza tra quanto riportato all'interno della CRR II e quanto previsto nel testo di Basilea.
In particolare nel EBA-RTS-2020-02 si richiede che il VaR utilizzato ai fini di *backtesting* sia calcolato utilizzando unicamente i fattori di rischio *modellable*, al contrario di quanto previsto da Basilea (paragrafo 10.30).
L'indicazione specifica dell'EBA RTS di includere solo i fattori di rischio *modellable* nel calcolo del VaR può essere intesa come la volontà del *Regulator* di rendere il più allineata possibile la misura di rischio oggetto di *backtesting* e la misura utilizzata per il calcolo del capitale, essendo comunque due metriche poco confrontabili fra loro.
La normativa permette tuttavia di escludere gli *overdrafts* derivanti da fattori di rischio *non modellable* dal conteggio ai fini di *backtesting*. Tale approccio potrebbe comportare problemi significativi: in primis, escludendo i fattori di rischio *non modellable*, è probabile che si generino svariati *overdrafts* associati a *non-modellable risk factor*, e questo potrebbe richiedere un aggravio potenzialmente significativo nelle analisi richieste dalle funzioni di controllo per catalogare gli *overdraft*; inoltre, un elevato numero di *overdrafts* eludibili potrebbe comportare una perdita di significatività dell'analisi di *backtesting*.
Inoltre, il fatto di calcolare un VaR che tenga in considerazione solo fattori di rischio modellabili è una complicazione addizionale, alla luce del fatto che, escludendo una porzione potenzialmente rilevante di fattori di rischio, tale metrica non costituirebbe una misura operativamente utilizzabile dal punto di vista gestionale.
Non è peraltro certo che l'esclusione dei fattori di rischio non modellabili dal calcolo del VaR ne riduca il valore in quanto l'esito del RFET potrebbe generare dei "*broken hedge*" tra fattori di rischio (modellabili e non), che nel confronto (*backtesting*) con gli APL e HPL (che comprendono tutti i fattori di rischio, modellabili e non) potrebbero condurre a risultati anche non prudenziali (ridurre la probabilità di *overdrafts*).

[4] In altri termini, non ci si attende una integrazione dell'approccio RNIME nel mondo FRTB.

Una possibile soluzione alternativa potrebbe prevedere l'inclusione all'interno del VaR di *backtesting* dei soli fattori di rischio per i quali sono disponibili dati con frequenza giornaliera. Tale posizione trova conferma all'interno del documento di risposta dell'*Industry* al *Consultation Paper* FRTB pubblicato nel marzo 2018 (sebbene questa non sia stata recepita all'interno della normativa comunitaria). Anche questa soluzione presenta comunque delle complicazioni, in quanto consisterebbe in un aggravio di controlli di qualità del VaR calcolato su un insieme esteso di fattori di rischio, ed allontanerebbe la misura oggetto di *backtesting* da quella usata per il calcolo del capitale.
Al momento non è prevedibile una modifica normativa, e sarà pertanto importante verificare la sostenibilità dei controlli di classificazione degli *overdrafts*. Infatti se la frequenza con cui si generano *overdraft* associati a non *modellable risk factor* è troppo alta, si potrebbero generare criticità operative, e potrebbe perdere di significatività lo stesso *backtesting*.

3.6 Capitalizzazione Non-Modellable Risk Factor: metodologia di calcolo

Con riferimento alla modalità di calcolo da adottare ai fini della capitalizzazione dei *Non Modellable Risk Factor*, (NMRF), l'EBA ha pubblicato a Dicembre 2020 un RTS ([4]) che definisce la metodologia che le istituzioni devono utilizzare per determinare i requisiti di fondi propri relativi ai NMRF nel nuovo *framework* di rischio di mercato (SES). Tale Regolamento, in estrema sintesi, disciplina:

- la determinazione di un periodo di *stress* per ogni *risk class*, con conseguente necessità di raccogliere i dati dei NMRF per il periodo di *stress* identificato;
- l'individuazione di differenti metodologie, applicabili a seconda della disponibilità (numerosità) dei dati di NMRF, ai fini dello sviluppo di scenari estremi di *shock* applicabili.

Le tematiche maggiormente dibattute all'interno dell'*industry* sono sostanzialmente le seguenti:

1. criteri di identificazione e calibrazione dello *stress period* per ogni *risk class*;
2. metodologia di calcolo in senso stretto ai fini della capitalizzazione dei NMRF: in particolare, si fa riferimento agli approcci delineati all'interno dell'EBA RTS di dicembre 2020 [4]: *Direct Method*, *Stepwise Method* (*Historical Approach* e *Asymmetrical Sigma Approach*) e *Fallback Method*.

Per quanto concerne il primo punto (identificazione *stress period*), il testo normativo prevede due possibili approcci percorribili, per ciascuna *risk class*:

a) massimizzazione direttamente del dato di SES;
b) massimizzazione della metrica di *Expected Shortfall* calcolata sui soli fattori di rischio *modellable* appartenenti al *Reduced Set of Risk Factor* (RSRF) e, mediante opportuni coefficienti di *rescaling*, applicazione per estensione al perimetro di NMRF.

Nell'[opzione *a)*] il periodo di *stress* è rappresentato dai 12 mesi (a partire almeno dal 1° gennaio 2007), calcolato per ogni *risk class*, che massimizzano la somma della *Rescaled Stress Scenario Risk Measure* (RSS) associata a fattori di rischio mappati a quella *risk class*. Con riferimento a tale opzione, al fine di ridurre gli oneri operativi per le istituzioni, l'EBA consente l'utilizzo di metodi "*sensitivity-based*" (in sostituzione dei più onerosi *full revaluation*).
Nell'[opzione *b)*] il periodo di *stress* è rappresentato dal periodo di 12 mesi (a partire almeno dal 1° gennaio 2007), calcolato per ogni *risk class*, che massimizza la *Partial Expected Shortfall* (PES) sull'insieme ridotto dei fattori di rischio modellabili appartenenti alla classe di rischio in oggetto. In tal caso le istituzioni sono tenute a fornire la prova che il periodo individuato (sui fattori di rischio modellabili) sia un periodo di *stress* finanziario anche per i NMRF della corrispondente *risk class*, mediante un approccio che sarà oggetto di convalida dal *Supervisor*.
La seconda metodologia [opzione *b)*] farebbe ricadere sulle banche una sorta di onere della prova ("*Institutions are required to provide evidence that the period identified is also a period of financial stress for NMRFs. The approach followed will be subject to authorities' validation during IMA approval process.*"), ossia la necessità di dimostrazione che il periodo di *stress* individuato sui *modellable risk factor* risulti valido per estensione anche ai *Non-Modellable Risk Factor*. In quest'ambito, tuttavia, il *Regulator* non fornisce alcuna linea guida in relazione a quale approccio intraprendere al fine di procedere a tale dimostrazione.
In virtù di tali considerazioni, quindi, si ritiene *best practice* di mercato la massimizzazione della misura di SES [opzione *a)*], in quanto non sussiste alcun tipo di ambiguità in termini operativi, poiché non viene richiesto alcun onere della prova alle istituzioni. Inoltre, al fine di superare le problematiche legate all'*effort* computazionale di questo approccio [opzione *a)*], lo stesso *Regulator* ammette la possibilità di adottare un approccio *sensitivity-based*, bypassando l'onerosità della *full revaluation*.
Riguardo alla metodologia di calcolo ai fini della capitalizzazione dei NMRF, il testo normativo (EBA RTS di dicembre 2020 [4]) prevede diversi approcci percorribili a seconda della disponibilità (numerosità) dei dati di NMRF nel periodo di *stress* individuato (corrispondente *risk class*):

i. *Direct Method*, utilizzabile in caso di presenza di almeno 200 rendimenti decadali;
ii. *Stepwise Method - Historical Approach*, utilizzabile in caso di presenza di almeno 200 rendimenti decadali;
iii. *Stepwise Method - Asymmetrical Sigma Approach*, utilizzabile in caso di presenza di almeno 12 rendimenti decadali;
iv. *Fallback Method*, utilizzabile indipendentemente dal numero di rendimenti decadali come "*fallback approach*".

Si rileva che nel momento in cui, a parità di qualità delle serie storiche (e.g. nell'ipotesi di disporre di almeno 200 rendimenti decadali per ciascun NMRF), risulta possibile far ricorso sia all'approccio *Stepwise Method - Historical Approach* che a quello di tipo *Direct Method*, analisi quantitative effettuate su alcuni campioni di portafogli costituiti da strumenti sia lineari che strutturati

con prevalenza di rischio *Interest Rate* (rappresentativi del portafoglio bancario), mostrano risultati in termini di *capital charge* con differenze trascurabili tra le due metodologie. Considerando che l'*effort* computazionale del *Direct Method* (che necessita di 250 *full revaluation* dell'intero portafoglio a livello di singolo fattore di rischio) risulta essere notevolmente più elevato rispetto allo *Stepwise Method - Historical Approach* (che richiede 4+2 *full revaluation* dell'intero portafoglio a livello di singolo fattore di rischio), *ceteris paribus* è possibile delineare come *best practice* di mercato l'adozione dello *Stepwise Method - Historical Approach*, in caso di presenza di almeno 200 rendimenti decadali.
Sebbene il *Direct Method* risulti infatti essere la stima più affidabile, non necessitando di calibrazioni degli *shock* e aggiustamenti di non linearità, tuttavia questo approccio richiede uno sforzo computazionale molto significativo, non giustificato dal potenziale risparmio in termini di *capital charge*, almeno secondo le stime ad ora disponibili dall'*industry*.
In generale il quadro proposto dall'EBA per capitalizzare i NMRF è percepito dall'*industry* come molto sofisticato ed estremamente impegnativo dal punto di vista computazionale. Inoltre dalle prime analisi effettuate, questo approccio sembrerebbe implicare un *capital charge* molto punitivo.

3.7 Livello di controllo sul Vendor

Nell'ambito dell'implementazione del *Risk Factor Eligibility Test* (RFET), le istituzioni hanno la possibilità di utilizzare tre fonti per la definizione dello status di modellabilità dei fattori di rischio:

- *Trade* effettivamente eseguiti dalla stessa istituzione con relativo set informativo necessario;
- *Committed Quote* eseguite dalla Banca stessa;
- possibilità di acquistare l'informazione (*Trade*/*Committed Quote*) sulla modellabilità all'esterno direttamente dai vendor.

Nel terzo caso, il livello di controllo che le istituzioni hanno sui vendor potrebbe essere un elemento critico in fase di approvazione del modello.
Il Regulator richiede infatti all'istituzione, che utilizza una terza parte per l'acquisizione dei dati necessari per il RFET, la verifica dell'esecuzione di un'analisi di audit indipendente sul vendor stesso ("*the institution has verified that the third-party vendor is subject, at least annually, to an independent audit by a third-party undertaking, within the meaning of Article 325bi(1)(h) of Regulation (EU) No 575/2013, regarding the validity of its price information, governance and processes, and has access to audit results and reports, in case these are requested by the institution's competent authorities."*).
Secondo la normativa il Data Provider deve essere assoggettato ad una verifica da parte di un auditor indipendente, mettendo a disposizione delle istituzioni una documentazione che certifichi l'esito di tale verifica.
In questo senso, l'orientamento prevalente sembra essere quello di rendere pienamente coscienti le istituzioni della qualità delle informazioni provenienti dall'esterno, ed evitare di avere modelli interni basati su elementi "*black box*".

Come ultima possibilità prevista dalla normativa, la banca può basarsi su eventuali vincoli contrattuali riguardanti le verifiche svolte internamente dal *data provider*: *"Where a third-party vendor does not provide the institution with the information to verify that a price is verifiable in accordance with paragraphs 1 and 2, the institution shall be able to demonstrate to its competent authority that the third-party vendor is contractually obliged to verify itself that a price is verifiable in accordance with paragraphs 1 and 2."*

Si sottolinea in questo ambito un punto critico: il limitato numero di vendor che offrono il servizio di *data provider* per l'attività di RFET dovrebbe assoggettarsi al dettato normativo il prima possibile, se non già *compliant*, in maniera da non generare difficoltà nei processi di validazione del modello interno messi in campo dalle banche.
Il rischio a cui si va incontro è che le banche siano impossibilitate ad ottenere risposte adeguate e tempestive dai vendor e siano di conseguenza messe sotto pressione dalle richieste del Supervisor.
Sotto questo punto di vista, il meccanismo ideale sarebbe un'interazione diretta tra il vendor e il Supervisor, ma questo è attualmente fuori dall'architettura normativa.
In virtù delle suddette considerazioni è valutata utile, come *best practice* di mercato, quella di prevedere – sin dal momento dell'eventuale stipula del contratto con il *Data Provider* – vincoli riguardanti la revisione indipendente del Vendor stesso.

4. Focus su P&L Attribution (PLA)

Il nuovo *framework* FRTB per quanto riguarda i modelli interni rende ancor più importante l'aderenza e la coerenza delle misure di rischio a quelle di mercato utilizzate dalle strutture di *front office* richiedendo, in ambito di *Eligibility Test* dei *desk*, oltre al *backtesting*, anche il superamento di due test di *P&L Attribution* (PLA).
L'obiettivo dei test è proprio quello di misurare le eventuali semplificazioni del modello interno utilizzato dalle istituzioni per il calcolo del requisito patrimoniale a fronte dei rischi di mercato in termini di differenze di modelli di valutazione e/o fattori di rischio mancanti rispetto a quelli utilizzati dai sistemi di *front office* ed evitare che tali eventuali semplificazioni portino ad una sottostima materiale del requisito.
Alla base dei PLA test ci sono due misure di P&L, l'*Hypothetical* (HPL) e il *Risk Theoretical* (RTPL).
Il primo (HPL) deve essere calcolato in base ai modelli di *pricing*, le parametrizzazioni, i dati di mercato e qualsiasi tecnica utilizzata dall'istituto nel processo di valutazione di fine giornata e deve includere tutti gli aggiustamenti che sono sensibili ai fattori di rischio di mercato che vengono aggiornati con frequenza giornaliera e che sono inclusi nel modello di calcolo dei rischi.
Il secondo (RTPL) è calcolato invece attraverso i fattori di rischio e il motore di calcolo dei rischi secondo il modello interno proprio del *Risk Management Engine*. In questo caso, quindi, si tiene conto di tutti i fattori di rischio inclusi nella stima dell'*Expected Shortfall* e di quelli considerati nel calcolo degli *Stressed Expected Shortfall* e si utilizzano i modelli di *pricing*, le parametrizzazioni e dati di mercato utilizzati in ambito IMA.
I test nel dettaglio sono eseguiti sulle serie di HPL e RTPL delle ultime 250 date di *trading* attraverso le seguenti due metriche:

➢ "*Spearman correlation*", che valuta il livello di dipendenza statistica fra due serie, misurandone la correlazione fra i ranghi;
➢ "*Kolmogorov Smirnov test*", che valuta la somiglianza delle distribuzioni di due serie storiche in assenza di ipotesi sulle distribuzioni.

In base ai risultati di questi test, rispetto a delle soglie stabilite, ogni singolo *desk* potrà essere dichiarato '*eligible*' ad entrare nel computo del requisito a IMA. In caso contrario, a seconda del valore assunto dai test rispetto alle soglie definite, il *desk* potrebbe andare a *Standard* o rimanere a IMA ma con applicazione di *Capital Surcharge*.
E' quindi di fondamentale importanza capire quali tipologie di disallineamento fra le architetture di *Front* e quelle di *Risk* potrebbero portare al fallimento dei test, anche alla luce del fatto che la normativa consente in alcuni casi specifici di allineare i dati di input per il calcolo delle due misure di P&L.

4.1 Gestione architetture separate Front – Risk e possibilità di allineamento dati di input per il calcolo di HPL e RTPL

L'utilizzo di architetture di *Front* e di *Risk* sostanzialmente diverse, sebbene consentito, risulta essere penalizzante secondo la nuova normativa che, attraverso i PLA test, richiede maggior presidio sulla capacità dei modelli interni di calcolo dei rischi di rappresentare il reale potenziale P&L dei *trading desk*, pena il passaggio del calcolo del requisito a Modello *Standard*.
Il caso estremo di architetture completamente separate, anche se meno frequente, porta ad importanti problemi di disallineamento delle misure di HPL e RTPL, perché oltre a potenziali differenze sui fattori di rischio, considera valutazioni di partenza potenzialmente diverse aggravando ulteriormente i casi di differenze già presenti anche nel caso di utilizzo di sistemi di calcolo analoghi.
La normativa, ribadendo che l'obiettivo di questi test è valutare la materialità delle semplificazioni del modello di *Rischio* e di eventuali fattori di rischio trascurati, ammette che alcune differenze potrebbero dipendere da disallineamenti nei dati di mercato utilizzati per il calcolo dei due P&L, quindi tali da non essere considerate come semplificazioni o mancanze. Per questa tipologia di scostamenti è pertanto consentito, sulla base di specifiche condizioni, un allineamento dei dati usati nel calcolo del RTPL con quelli usati nell'HPL.
Di seguito quanto indicato nell'RTS *on Backtesting and PLA requirements*:

"In particular, the draft RTS identify two cases where the institution may be allowed to align the data:

1. *The institution may use the HPL input data as input data for the RTPL for a given risk factor (e.g. zero rate tenor x) that is included in both the RTPL and the HPL where:*
   a. *the input data used in the RTPL and HPL to derive the value of the risk factor are of the <u>same nature</u> (e.g. par rate tenor x);*
   b. *the differences in the value of the input data are due to either <u>different providers of market data</u> (e.g. par rate tenor x taken from provider A in the HPL computation and par tenor x taken from provider B in the APL computation) <u>or different time fixing of market data</u> sources.*

2. *The institution may substitute the value of a risk factor used in the calculation of the RTPL with the value taken by the same risk factor used in the calculation of the HPL as long as:*
   a. *in the calculation of the HPL, the value taken by the risk factor has been derived, transforming input data into suitable data for that risk factor (in other words, in the computation of the HPL, the risk factor does not directly correspond to the input data);*
   b. *the value of the risk factor in the HPL has been obtained using techniques of the valuation systems used for the hypothetical changes in the trading desk portfolio's value;*
   c. *none of the techniques of the valuation systems used for computing the HPL have been rebuilt in the valuation systems to derive the value of the risk factor for computing the RTPL."*

Tra i potenziali casi di differenze, oltre all'esempio riportato in normativa, ci sono quindi quelli che possono essere ricondotti facilmente alle due casistiche previste, tra cui i casi di differenti *time fixing* o *market data provider* (a patto che abbiano la stessa natura) e casi un po' più ambigui come quelli relativi a:

- tutte le posizioni che lato *front-end* sono valutate a *mark-to-market* mentre lato *risk*, partendo dal valore di mercato, vengono rivalutate a teorico al fine di determinare lo *shocked value* nelle misure di ES e SES e di conseguenza anche per il calcolo del RTPL;
- i fattori di mercato che in ambito ES sono stati ricostruiti attraverso una *proxy*;
- i fattori di mercato, anche non modellabili, che presentano poche osservazioni giornaliere per le quali le fonti e le frequenze di aggiornamento potrebbero differire fra *front* e *risk* (questo caso potrebbe ricadere in quello generico di *provider* di *market data* differenti).

Un esempio concreto del primo punto di cui sopra è quello di un bond prezzato a *mark-to-market* sui sistemi di *front* che nei sistemi di calcolo dei rischi è valutato a teorico al fine di poter stressare tutti i fattori di rischio sottostanti (in particolare le curve di tasso d'interesse e quelle di *spread* di credito dell'emittente) a cui il prezzo del bond è esposto. Il motore di calcolo dell'ES per lo *spread* di credito utilizzerà gli *shock* di una curva *issuer* (ottenuta mediante *bootstrapping* di tutti i titoli riferiti a

quell'emittente/*seniority*/*currency*) che potrebbe non essere completamente coerente con il movimento, a parità di data, dello *spread* implicito nel prezzo di mercato del bond in oggetto. Quest'ultimo (*shock* specifico del *credit spread* del bond) è comprensivo di altri elementi, quali ad esempio la liquidità specifica del bond in oggetto o componenti di strutturazione, che nella curva emittente vengono "mediati" insieme a quelli degli altri titoli *constituent* determinando potenziali differenze nello specifico. Inoltre la qualità degli *spread* della curva *issuer* dipende anche dalla numerosità e qualità/liquidità dei bond su cui viene costruita e risulta quindi inferiore per gli emittenti più piccoli come *small corporate*. La normativa in questo modo incoraggia le istituzioni a migliorare la qualità delle curve emittenti e delle eventuali *proxy* utilizzate, sebbene in alcuni casi sia comunque impossibile arrivare ad una piena coerenza con le variazioni registrate sui prezzi di mercato, andando quindi a penalizzare, ad esempio, *desk* maggiormente esposti a *small corporate*, che fallendo i PLA test dovranno essere capitalizzati secondo il metodo *standard*, con *risk weight* penalizzanti (che vanno dall'1,5% al 12%). Allo stesso modo *desk* esposti a *market data* ricostruiti in *proxy*, come ad esempio volatilità illiquide di sottostanti *equity*, potrebbero ricadere sul modello *standard* sebbene l'esposizione a questi fattori di rischio possa essere marginale.
In conclusione, sebbene la normativa consenta alcuni allineamenti dei *market data* utilizzati nel calcolo del RTPL con quelli dell'HPL, permangono difficoltà e/o impossibilità ad adeguare le modalità di calcolo dei due differenti motori, sebbene coincidenti, per casi in cui le differenze siano inevitabili per costruzione.

4.2 Tipologia di desk che potrebbero presentare maggiori problematiche

Riprendendo quanto già introdotto nella sezione precedente, nell'ambito del superamento dei test di *P&L Attribution*, molte istituzioni si trovano ad affrontare delle casistiche di *desk* caratterizzati da dati di P&L "patologici", che a priori possono essere considerate come a probabile rischio di fallimento dei test. I principali punti d'attenzione sono i seguenti:

- portafogli che presentano degli *hedge* molto rilevanti, che possono risultare problematici in quanto viene meno il segnale associato al movimento dei fattori di rischio sottostanti, mentre sono accentuate le basi ed altre componenti di rumore del P&L;
- *desk* in cui sono presenti scostamenti tra i *market data* utilizzati lato *front office* e lato *risk management*. In questo caso, la normativa consente di apporre delle correzioni in modo da generare convergenza nei *market data*, così da garantire un buon allineamento (si fa riferimento alla normativa già citata nel paragrafo 4.1). A titolo d'esempio, nei *desk fx* può essere utilizzato il tasso di cambio ad orari differenti (*Reference Price vs Closing Price*);
- *desk* in cui sono presenti strumenti sensibili a parametri di mercato per i quali nei sistemi di *Risk Management* occorre fare ricorso a *proxy*.

Con riferimento al primo punto, benché tale problematica caratterizzasse anche le misure di PLA test originariamente definite dalla FRTB (*Mean and Variance Ratio*), non è atteso un intervento da parte del *Regulator*: pertanto, una potenziale soluzione condivisa come *best practice* di mercato è quella di tenere in considerazione tali tecnicalità al momento della definizione della struttura *target* dei *trading desk*.
Con riferimento al secondo punto invece, nel documento di RTS del marzo 2020, EBA ammette la possibilità di allineare il *set* di input utilizzati per il calcolo dei dati di P&L lato *Front Office* e *Risk Management*, laddove siano soddisfatte determinate condizioni (e.g. se i dati di input utilizzati nel calcolo di RTPL e HPL per derivare il valore del *risk factor* hanno la stessa natura o se la differenza dei dati di input sia imputabile ad un diverso *provider* di *market data*). Questo è discusso in dettaglio nel paragrafo 4.1.
Con riferimento al terzo punto, infine, il ricorso a *proxy* nell'ambito dei sistemi di *Risk* dovrebbe essere il più preciso possibile in termini di rappresentazione della *proxy* del reale fattore di rischio di mercato. Pertanto, al fine di rendere l'esito positivo dei PLA Test più probabile, è molto importante che le istituzioni sviluppino un processo di assegnazione e monitoraggio delle *proxy* che consenta una rappresentazione più vicina possibile del fattore di rischio "oggetto di *proxy*".

4.3 Confronto con attuale Representative Portfolio Backtesting

La CRR II, in continuità con la normativa precedente e nell'ambito della validazione del modello interno, richiede di identificare portafogli ipotetici rappresentativi dell'attività dell'istituzione, in modo da verificare la presenza di particolari problematiche in termini di rischio di concentrazione, di *material basis* oppure a livello di rischi associati all'uso di *proxy* all'interno del modello. La normativa infatti cita all'articolo 325bj comma 3 il seguente testo:

3. The validation of the internal risk-measurement models of an institution shall not be limited to back-testing and P&L attribution requirements, but shall, at a minimum, include the following:

(a) tests to verify whether the assumptions made in the internal model are appropriate and do not underestimate or overestimate the risk;
(b) own internal model validation tests, including back-testing in addition to the regulatory back-testing programmes, in relation to the risks and structures of their portfolios;
(c) the use of hypothetical portfolios to ensure that the internal risk-measurement model is able to account for particular structural features that may arise, for example, material basis risks and concentration risk, or the risks associated with the use of proxies.

Analisi dettagliate sui portafogli ipotetici hanno anche lo scopo di identificare possibili anomalie non visibili a livelli di portafoglio aggregati, quindi a livello di *desk*.
In questo contesto, rispetto alla normativa corrente, la CRR II introduce quindi la necessità di analizzare i portafogli ipotetici anche dal punto di vista della *P&L Attribution*, e non solo di *backtesting*. In virtù del fatto che le logiche richieste dal *framework*

FRTB risultano inevitabilmente più complesse rispetto al contesto attuale, risulta essere necessario delineare in maniera puntuale le caratteristiche utili all'identificazione dei suddetti portafogli ipotetici. Per quanto concerne le analisi di *backtesting*, le logiche per la costruzione dei portafogli non andranno a scostarsi di molto rispetto a quanto avviene attualmente, mentre l'introduzione della P&L Attribution porterà necessariamente ad una scelta parallela più mirata dei portafogli ipotetici. Tale approccio può avere come punto di partenza quanto constatato all'interno del paragrafo precedente in merito ai *desk* potenzialmente più problematici (e.g. *desk* in cui vi è una elevata presenza di *bond* o caratterizzati dalla presenza di NMRF o utilizzo di *proxy*).

5. Focus su Default Risk Charge (DRC)

5.1 Impatti dell'introduzione dell'Equity (strumenti complessi) e look through approach Index e multi underlying option per il calcolo del Jump To Default

Una delle principali differenze con i modelli IRC del framework Basilea 2.5 è la necessità di estendere il perimetro oggetto della misura DRC (FRTB) anche agli strumenti equity. Questa estensione introduce ulteriori elementi di complessità da gestire nel modello, associato all'importanza di strumenti multi-underlying e/o payoff non lineari tipici della classe di rischio equity nei portafogli di negoziazione.
Ad esempio, calcolare la P&L di un'opzione su indice (e.g. un comunissimo STOXX50), tenendo conto dei fallimenti congiunti delle aziende costituenti l'indice stesso, risulta molto pesante dal punto di vista computazionale. In linea di principio, per simulare l'impatto di P&L di un derivato con payoff non lineare su un paniere di emittenti, si richiederebbe il calcolo di un prezzo per ciascuno scenario (*MonteCarlo path*).
Tenendo conto del numero di scenari che plausibilmente saranno necessari per una stima stabile e a convergenza della misura (numero di simulazioni MonteCarlo, e.g. dell'ordine di grandezza del milione), il volume di prezzi richiesti per la simulazione dell'intero portafoglio rischia di superare i limiti di fattibilità.
Al fine di indirizzare l'effort computazionale legato alla necessità di dover applicare delle tecniche simulative (i.e. Montecarlo) per il pricing dei suddetti strumenti, il paragrafo 33.32 del BCBS Final Text di gennaio 2019 consente l'utilizzo di approcci semplificati limitatamente ai *multi-underlying instruments*:

"*The bank's model must reflect the non-linear impact of options and other positions with material non-linear behavior with respect to default. In the case of equity derivatives positions with multiple underlyings, simplified modelling approaches (for example modelling approaches that rely solely on individual jump-to-default sensitivities to estimate losses when multiple underlyings default) may be applied (subject to supervisory approval).*"

Tuttavia è possibile individuare due punti di discussione all'interno dell'industry:

- innanzitutto, la suddetta normativa non fornisce specifiche linee guida in merito alla tipologia di approcci semplificati da utilizzare in tale ambito;
- in secondo luogo, la possibilità offerta dal testo BCBS non risulta riportata esplicitamente all'interno della CRR II, lasciando quindi una potenziale discrezionalità interpretativa al Supervisor europeo.

Allo stesso tempo potrebbero verificarsi delle situazioni in cui l'adozione di un approccio semplificato (per mezzo ad esempio di *partial revaluation*) porti ad assunzioni eccessivamente approssimative, che quindi si tradurrebbero in un pricing non corretto e di conseguenza comporterebbero stima di impatti di P&L che distorcerebbero la metrica DRC. Una linearizzazione delle metodologie di calcolo effettuata applicando uno shock prestabilito, ad esempio, verosimilmente darebbe luogo a misure di *Jump to Default* (JtD) non realistiche, che nel caso di portafogli costituiti in buona parte da strumenti esotici, potrebbero condurre a risultati fuorvianti.
Allo stesso modo, benché l'adozione di una griglia di valori di default (in termini di shock sull'indice e relativo impatto di *pricing* sullo strumento) e la conseguente adozione di tecniche di interpolazione possa essere considerata come una *best practice* di mercato tale da ridurre il costo computazionale, essa non rappresenta una soluzione totalmente risolutiva poiché richiederebbe comunque un numero elevato di full revaluation per gli strumenti multi-name, pari ad almeno il numero di punti della griglia adottata.
Qualunque soluzione metodologica di approssimazione delle funzioni di pricing non porterebbe a benefici sostanziali considerato comunque il grande costo operativo di mantenimento delle anagrafiche necessarie alla gestione di indici e strumenti multi underlying nell'ambito del look-through approach: ogni indice può corrispondere a decine o centinaia di singoli emittenti da censire nelle anagrafiche interne.

5.2 Indirizzare al Regulator i punti dubbi della normativa (e.g. Rivalutazione di multi-name)

In aggiunta alla mancata trasposizione esplicita (all'interno della CCR2) della possibilità di effettuare un pricing semplificato degli strumenti multi-name, è rilevato un altro punto problematico dell'attuale assetto normativo: la apparente inconsistenza nel trattamento del DRC tra approccio standard e modello interno.
Infatti:

- nel contesto DRC SA è possibile porre a 0 il Risk Weight di alcune esposizioni (cfr. art. 22.7 BCBS, "*Claims on sovereigns, public sector entities and multilateral development banks may, at national discretion, be subject to a zero default risk weight in line with paragraphs 7 through 15 in the Basel III credit risk framework. National authorities may apply a non-zero risk weight to securities issued by certain foreign governments, including to securities denominated in a currency other than that of the issuing government*"), mentre tale possibilità non è applicabile al framework IMA;

- nel contesto SA vi è inoltre la possibilità di applicare dei coefficienti di ponderazione in relazione alla maturity degli strumenti inferiori all'anno (beneficiando quelli short term), possibilità non prevista invece in ambito IMA;
- nel framework IMA infine vi è la necessità di applicare un floor di 3bps ai dati di PD impiegati (cfr. art. 33.24, "*PDs are subject to a floor of 0.03%*").

Vi è quindi la concreta possibilità che alcune configurazioni di portafoglio risultino trattate in maniera significativamente diversa tra l'approccio standard ed il modello interno, generando impatti difformi in termini di metrica DRC. Ad esempio, per portafogli long sul debito sovrano o per portafogli long su titoli obbligazionari finanziari con scadenza inferiore all'anno, la misura potrebbe risultare innaturalmente superiore nel modello interno, per importi anche importanti.
Il framework SA per quanto riguarda il DRC sembrerebbe quindi essere più benefico, andando a disincentivare per alcuni desk l'utilizzo del modello interno. A dimostrazione di quanto espresso sono state effettuate *what-if analysis* dalle diverse istituzioni, che hanno manifestato impatti rilevanti. Sarebbe opportuno un migliore allineamento tra i trattamenti standard e del modello interno a livello normativo, al fine di non scoraggiare l'adozione del secondo specialmente con riferimento ad alcuni desk.

5.3 Coerenza con Credit Risk

La CRR II richiede che i valori di PD ed LGD da utilizzare come dati di ingresso nel modello siano quelli prodotti dai modelli di rischio di credito IRB, ove validati. In assenza di PD ed LGD provenienti dai modelli interni del credito, le istituzioni possono fare affidamento a eventuali modelli alternativi, o a fonti esterne. Pertanto la normativa definisce un chiaro ordine gerarchico di utilizzo delle fonti con riferimento ai parametri in questione[5]. La tematica è discussa in un Consultation Paper dell'EBA (EBA/CP/2020/12).
Questa richiesta normativa genera un legame potenzialmente problematico tra il rischio di mercato ed il rischio di credito. Due casistiche in particolare possono essere sorgente di difficoltà:

- emittente nel perimetro del trading book che è coperto da un modello IRB come categoria, ma per cui non è disponibile una PD o una LGD;
- emittente nel perimetro del trading book per cui non è validato un modello IRB.

Nel primo caso, l'istituzione è già autorizzata a generare una PD o una LGD per l'emittente, ma vi potrebbe essere una discrasia tra i tempi tecnici lato rischio di credito ed il tempo di permanenza nel portafoglio lato rischio di mercato. I parametri non saranno disponibili per un certo periodo, per cui sarà necessario utilizzare una diversa sorgente in attesa dei valori IRB. Dipendentemente dalla velocità di rotazione del portafoglio, si potrebbe generare una coda di richieste di PD/LGD che, alla fine del processo, potrebbero anche rivelarsi non più utili, a causa dell'uscita dell'emittente dal portafoglio. Ne conseguirebbe un significativo aggravio operativo.
Nel secondo caso non esiste un modello IRB con cui calcolare PD o LGD, e l'istituzione deve necessariamente ricorrere ad una sorgente alternativa.
In entrambi i casi, la normativa è estremamente chiara nel richiedere che le sorgenti alternative, che siano modelli interni specifici e limitati al perimetro DRC o fornitori esterni, devono soddisfare i medesimi livelli di qualità di un corrispondente modello IRB (CRR II, Articolo 325bp, e EBA/CP/2020/12, Articoli 1 e 2). Se la richiesta è coerente con il fine di mantenere il *level playing field* tra banche con e senza approvazione IRB, allo stesso tempo può generare un corto-circuito tra rischio di mercato e rischio di credito.
Infatti, se il principio è quello di garantire un livello di qualità equivalente a quello IRB, le istituzioni dovranno dotarsi di metodologie e processi analoghi. Si potrebbe quindi giungere alla situazione innaturale in cui un'istituzione disponga di una metodologia approvata dal Supervisore per il calcolo di PD e LGD nell'ambito DRC, ma ne sia invece sprovvista lato rischio di credito. In generale, l'approvazione del modello interno per il DRC potrebbe avere quindi significative conseguenze anche sulle politiche di estensione dei modelli IRB nel rischio di credito.
In aggiunta alla problematica più strutturale di interazione tra rischio di mercato e rischio di credito, vi è anche la tematica operativa di verifica e mantenimento della qualità e della coerenza PD/LGD utilizzate nel DRC, che aumenta ulteriormente lo sforzo e la complessità di gestione del modello.

5.4 Problematiche di calibrazione

La prima problematica di calibrazione riguarda la discrezionalità nella possibilità di applicare Liquidity Horizon inferiori all'anno su portafogli Equity, senza tuttavia che siano fornite ulteriori specificità.
Tale discrezionalità implicherebbe impatti sull'operatività e sul modello con la necessità di andare a catturare dei potenziali default in un time-step inferiore all'anno, rendendo ulteriormente complesso il modello.
È quindi necessario comprendere i criteri con cui può essere concessa tale discrezionalità, poiché un approccio univocamente prudenziale, che dipende dall'esposizione dei portafogli, non è applicabile (e.g. l'applicazione di un Liquidity Horizon di 60 giorni potrebbe avere conseguenze diverse sulla metrica in funzione della direzionalità del portafoglio).
Non è identificabile una *best practice* di mercato, in quanto le istituzioni risultano essere ancora in una fase di studio anche in attesa della pubblicazione della CRR III.

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[5] Laddove l'emittente il cui default è oggetto di simulazione non rientra nel perimetro di calcolo del Rischio di Credito con IRB la banca ha la possibilità di utilizzare il secondo approccio nell'ordine di priorità definito dalla normativa (ovvero utilizzando dati rivenienti da data provider esterni). Tuttavia, nel momento in cui il suddetto emittente dovesse in seguito essere coperto dai modelli IRB, l'istituzione dovrebbe fare ricorso alla prima fonte gerarchica (appunto dati IRB). Tale metodologia potrebbe però comportare potenziali problematiche di discontinuità con inevitabili impatti sulla metrica di Capital Requirement.

Una seconda problematica di calibrazione riguarda la richiesta di disporre di un modello che tenga conto della correlazione tra Recovery Rate e PD (cfr. articolo 325bp, par.2 della CRR II), la quale richiede una calibrazione estremamente complessa da implementare in termini operativi. Una soluzione proposta da alcune istituzioni è quella di generare un Recovery Rate che dipenda dal *credit worthiness* dell'emittente attraverso l'utilizzo di barriere calibrate in funzione delle PD.
Resta comunque aperto il discorso su come dimostrare la solidità del modello adottato, che è difficilmente validabile dal punto di vista statistico dato il livello di complessità richiesto e la scarsità di dati a disposizione.

5.5 Validazione della misura

Come descritto nei punti precedenti, secondo il tavolo risulta complesso fornire una valutazione statisticamente robusta in merito alla bontà o meno del modello adottato.
A causa del livello di confidenza e dell'orizzonte temporale della misura, non è infatti possibile effettuare *back-testing* su un modello di questo tipo e, dunque, si ritiene che tale tematica potrebbe essere oggetto di *finding* del Regulator nel caso la metodologia adottata non dovesse essere considerata robusta.
Come già visto per il modello IRC, in particolare a partire dalle ispezioni TRIM, la validazione del modello sarà estremamente complessa ed articolata, richiedendo un elevato numero di test. Viene infine sottolineato, come si evince sia da BCBS (paragrafo 33.34) sia da CRR II (Articolo 325bp), che molta enfasi è stata posta sul rischio di concentrazione, aspetto importante della metrica DRC.
Stress test e *sensitivity analysis* focalizzate su tale rischio sembrano quindi rappresentare un tassello imprescindibile nella validazione del modello.

6. Conclusioni

Sebbene negli ultimi mesi il framework normativo sui rischi di mercato abbia raggiunto un livello di consolidamento e maturità significativo, persistono tuttora delle complessità nella finalizzazione dell'impalcatura metodologica da parte delle istituzioni finanziarie. Infatti, in attesa del recepimento dei dettami regolamentari FRTB a livello comunitario con la pubblicazione della CRR III, lato industry sono ancora in atto discussioni in merito alle technicalities e specificità del nuovo modello interno.
Alla luce delle suddette considerazioni, l'iniziativa della Commissione Congiunta AIFIRM - ASSIOM FOREX sul tema IMA FRTB ha mostrato che le banche convergano verso delle *best practice* di mercato comuni sulla maggior parte delle tematiche oggetto di analisi, tanto metodologiche quanto organizzative. Ciò nonostante, sussistono comunque ulteriori elementi di discussione (attinenti ad esempio al costo computazionale relativo al calcolo delle componenti di NMRF e di DRC, ma anche discrasie normative tra BCBS Final Text e CRR) che dovranno essere indirizzati al Regulator.
Non ad ultimo, i recenti interventi normativi si sono orientati verso un alleggerimento del capital requirement derivante dall'applicazione dello Standardised Approach (SA) limitando, in virtù del maggiore effort operativo e degli impatti in termini di capitale, gli incentivi all'adozione del modello interno. In sintesi quindi, sebbene il go-live del reporting IMA FRTB sia atteso non prima di gennaio 2024, è fondamentale che vengano chiariti i punti normativi attualmente *pending* cosicché le banche possano consolidare le implementazioni on-going e garantire la compliance al nuovo contesto regolamentare.

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Money laundering transaction detection with classification tree models

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Abstract

The detection of money laundering is a very important problem, especially in the financial sector. We propose a mathematical specification of the problem in terms of a classification tree model that ”automates” expert based manual decisions. We operationally validate the model on a concrete application that originates from a large Italian bank. The application of the model to the data shows a good predictive accuracy and, even more importantly, the reduction of false positives, with respect to the ”manual” expert based activity. From an interpretational viewpoint, while some drivers of suspicious laundering activity are in line with the daily business practices of the bank's anti money laundering operations, some others are new discoveries.

Keywords: Classification Trees, Automatic laundering detection, Predictive accuracy

1. Introduction

Money laundering embraces all those operations that disguise the illicit origin of capital flows, giving them a semblance of legitimacy, to facilitate the subsequent reinvestment in the ”legal” economy.

Money laundering is a very important problem for the society. It is estimated that 2-5% of global GDP is laundered annually, with an overall recovery rate of illicit assets at just 1.1% in Europe, according to Europol.

Given the central role of financial intermediaries such as banks, insurance companies and asset managers in the management of capital flows, authorities and regulators focus their surveillance on them. The detection of money laundering thus becomes of uttermost importance for financial intermediaries, whose daily activities should be monitored to avoid money laundering transactions.

To achieve this aim, financial intermediaries have established internal functions targeted towards the preventive measurement of anti money laundering risks, with the mission of marking as “suspicious” the transactions with the highest risk. The identification of a transaction as suspicious may have several consequences, from the the bank account of the originator of the transaction being frozen, to the opening of a legal case.

Against this background, a financial intermediary should develop a data driven statistical model to detect suspicious transactions that, while correctly identifying all possible laundering cases, avoiding a type I error, does not lead to an excessive number of susspicious cases, which may lead to a reputational loss for the intermediary (type II error).

The literature on the topic of money laundering stems from the context of fraud detection. For a general review see, for instance, the contributions of Bonini et al. (2019) and Chen et al. (2014) or, from a statistical viewpoint, Bolton and Hand (2002), Sudjianto et al. (2010) and, from a computer science viewpoint, Luo (2014) and Wang and Yang (2007).

Fraud detection methods are suited to model situations in which the cases of actual fraud are known, and the aim of statistical methods is to discover the most frequent patterns that have led to the fraudolent cases, in an unsupervised setting, for which the variable to predict is unknown.

Financial intermediaries, however, are not interested only in estimating the probability of a laundering fraud but also in minimising the probability of an unnecessary identification of a transaction as a suspicious one.

Our aim is to tackle this problem and provide a model to classify each financial transaction as being ”suspicious” or ”not suspicious”. From a statistical viewpoint, our response variable to predict is not the event ”laundering”, which may also be very rare, and may take long time before being ascertained; but, rather, the event ”suspicion of laundering”.

The latter event is measurable, as the money laundering function of the intermediary has, by law, to identify, every day, which are the ”suspicious” transactions.

Given the difference in magnitude between amount of suspicious transactions and the amount of actual laundering transactions, our proposed model can be a supervised learning model, rather than an unsupervised one, in which the variable to be predicted is the suspicious flag event.

We remark that classifying transactions as ”suspicious” or ”non- suspicious” with expert-provided training labels is an objective which is different from the actual money laundering detection in banking transactions. Although different, it is worth pursuing, as the activity of providing expert based labels of ”suspicion” is customarily done by banks of all size, in a labor-intensive labeling of training data which may not always be practical and that, for prudentiality reasons, typically over estimates actual money laundering cases. From an operational viewpoint, the over estimate can lead to a false positive rate of about 90% (as reported by an Italian bank) which implies a cost which is economic and reputational, as the account of a suspicious customer may be temporarily frozen.

Our proposed statistical method, which generates ”automatic” suspicion rules from the ”manual” expert based activity, can thus be built and optimised not only as a tool aimed at accurately predicting expert's labels but also to reduce the false positives generated by the experts: cases detected as suspicious when they are not.

The only paper, to our knowledge, in line with our approach, is the recent paper by Jullum et al. (2020). Similarly to them, not only we propose a novel model to detect suspicious laundering activities, but we also validate it on on a concrete application, that originates from a large bank. While Jullum et al. (2020) considered data from DNB Bank, in Norway, we consider data from UBI Bank, in Italy.

Our added contribution to Jullum et al. (2020) is a model that distinguishes companies from individual customers, and provide different predictive rules for them. Furthermore, by using, as a response variable, the ”suspicion” that a certain transaction is a laundering, as declared by the responsible people within the bank, we contribute to ”automatise” human decisions by means of an artificial intelligence method. We thus contribute to the literature on explainable AI models (see for example, Giudici and Raffinetti, 2020) by comparing human learning with automated learning.

2. Methods

The detection of money laundering suspicions can be embedded into the field of credit scoring models, common in the credit risk literature, following the seminal papers of Altman (1968) and of Merton (1974). For a review see e.g. Resti and Sironi (2007)

The most commonly used model for credit scoring applications is logistic regression, based on generalised linear models (see e.g. Mc- Cullagh and Nelder, 1989; Agresti, 1992), specified by a Bernoulli response random variable and a logistic link function, which relates a function of the expected value of the response variable to a linear combination of the available predictor variables. In our context, the event "suspicious laundering", as previosuly defined, can be represented by a Bernoulli random variable with a parameter that indicates the probability that a transaction of a given customer is suspicious.

Logistic regression models are based on a link function that corresponds to the log-odds of the probability and its complement, with respect to the explanatory variables. The predicted probability of money laundering can then be obtained converting the estimated log-odds regression coefficients using the logistic function.

To improve the predictive accuracy of scoring models, we employ a machine learning model and, specifically, a classification tree, instead of a logistic regression model, similarly to Jullum et al. (2020).

Differently from logistic regression, a tree model is non parametric and does not require the assumption of a distribution for the response variable. A tree model is essentially an algorithm which partitions the available data recursively in subgroups (determined by the values of the explanatory variables). The partitioning stops when a further split of the sample does not significantly improve the within group homogeneity. For a review on tree models, and a comparison with logistic regression, also on a credit scoring case, see Giudici (2003).

Machine learning models are typically better in predictive accuracy, with respect to logistic regression models, and our work on UBI Bank data confirm this intuition. On the other hand, machine learning models may be more difficult to explain, being usually ”black boxes”. Differently from Jullum et al. (2020) we compare alternative tree models, but select only one among them: the most accurate in predictions, instead of taking an ensemble model, such as a random forest, which may not be so transparent. We also compare our results with the experience of the money laundering professionals of the Bank, and this provides a very good practical validation of the usefulness of the model.

Most of our application work has focused on feature engineering and variable selection. We have first built, from the original database of all customers of the bank, two databases: that of companies and that of individuals. This because they have different features, corresponding to different degrees of accountability: higher for companies, lower for individuals.

For both databases we have then randomly split the sample into a ”training” sample (80% of the data) and a ”validation” sample (20% of the data). As the observed percentage of cases is low (around 3%) we have under sampled the not suspicious cases to obtain a balanced sample.

For both databases we have taken all the continuous available data (summarising aggregate monthly volumes of transactions) as they were. Differently, for the qualitative data (describing the ”de- mographic” status of companies or of individuals) we have chosen to aggregate them in the grouping that is the most predictive of the target variable. We have then associated a binary dummy variable to each group.

We have then compared alternative tree models, calculating for each of them, on the same test set, the Area Under the ROC Curve as a measure of predictive accuracy, as well as the False Positive and True Negative rates. When the AUROC were similar, we chose the model with the lowest False Positive rate and, possibly, the lowest complexity.

3. Application

The main problem of the Bank is to identify in advance customers

with suspicious operations, to be reported for suspected money laundering activities. The identification should target the highest number of fraudolent cases but keeping unnecessary reports to a minimum. To this aim we build a predictive statistical model which, based on the reports submitted in the past (taken as a response variable) and on customers' transactions (taken as explanatory variables) recognizes automatically suspected customers.

The considered data consists of all transactions automatically alerted by the Information Systems of the bank in the years 2019-2020. Each transaction has been mapped to a specific customer ID. For the same customer we collected information on whether the Anti Money laundering function of the Bank have flagged the customer as ”suspicious” or not during the year 2020. For the response variable, we consider only the year 2020, as the decision to flag a customer as suspicious is usually taken looking at its transactions in the past year.

The total number of considered customer alerts is equal to 96624 among which 723 have been flagged as ”suspicious”. About 53% of the customers are companies and the remaining 47% individuals. The bank transactions of each customer have been classified according to the common standards in use into a series of binary variables. Besides transaction variables, each customer has ”demographic” variables, such as the economic sector of activity, and the legal nature, for the companies; the market segment, profession and age, for individuals. The total number of considered variables are: 46 for individuals and 184 for companies.

Once data has been prepared for the application of classification tree models, it has been split into a 80% training set, on which to build models, and a 20% validation set, on which to calculate model predictions, and select the best model, comparing the predictions with the actual values, in the ROC curve model comparison setting. Precisely, we have selected the tree model with the highest value of the AUROC curve, as suggested by Hand, Mannilla and Smyth (2001). In case of ”similar” values of the AUROC, we have chosen the model with the lowest value of the false positive rate, as one of our main objectives is to reduce the over identification of cases. When also false positive rates were similar, we have chosen the model with the most parsimonious model, for the sake of explainability and interpretability.

For the companies, the best selected model contains 10 final classes (leaves of the tree), with an AUROC equal to 0.81. and a false positive rate of 0.43. A model with 15 classes has a higher AUROC of 0.84 and a better false positive rate of 0.35: however, the management of the Bank has decided that the increased complexity and cost of its possible implementation exceeds its limited accuracy advantage.

The selected model is described in Figure 1. The relative impor- tance of the variables that have been selected is described in Table 1. The importance of a variable is defined by the reduction in the residual sum of squares reduction determined by the variable splits in the tree.

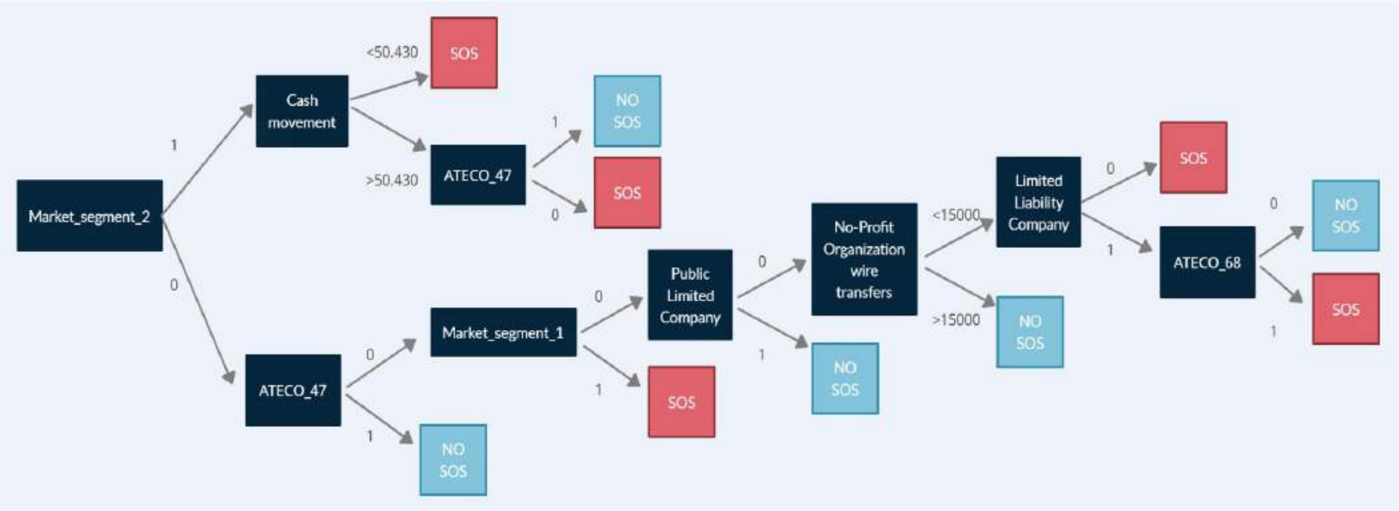

Figure 1: Final tree model - Companies.

ID	Variable	Relative importance
1	Medium size companies	1
2	Small size companies	0.93
3	Retail sector (excluding cars and motorcycles)	0.85
4	Limited liability companies	0.75
5	Real estate business sector	0.63
6	Non profit organisations	0.61
7	Public limited companies	0.53
8	Cash movements	0.52

Table 1: Final tree model - Companies.

From Figure 1 and Table 1 note that the most important variables that determine whether a company performs suspicious operations, in terms of money laundering, have mainly to do with the size of the company, its sector of activity, and its legal form: all ”demographic” variables. The only relevant transaction variable is the amount of cash movements. While the result on cash is in line with the daily practice and experience of the bank, is was somewhat unexpected that ”cash” is the only transaction amount that matters. The findings on the important demographic variables are instead new discoveries, not used in routinely applications. This concerns in particular the relevance of the retail sector: a driver of suspicious activity which is likely related to the type of customers of the bank, concentrated in an Italian region specialised in retail manufacturing. Another unexpected finding concerns the high risk attributed to non profit organisations: again, there is a large presence of these institutions in the regions where the bank operates.

For the individuals, the best selected model contains 15 final classes (leaves of the tree), with an AUROC equal to 0.77, slighlty inferior than for the companies, and with a false positive rate of 0.70, rather higher.

A model with 20 classes has a lower AUROC of 0.69 and a better false positive rate of 0.42: the management of the bank has decided that the increased complexity and cost of its possible implementation exceeds its limited accuracy advantage.

The chosen model is in line with the fact that the ”demographic” information on the companies are more standardised. The selected model is described in Figure 2. The relative importance of the vari- ables that have been selected is described in Table 2. The importance of a variable is defined by the reduction in the residual sum of squares reduction determined by the variable splits in the tree.

From Figure 2 and Table 2 note that the most important variables that determine whether an individual performs suspicious operations, in terms of money laundering, have to do with the market segment of the individual, its profession, and its age: “demographic” variables. In addition, three transaction variables are important: the relevant amounts (in cash); the account balance (in a month) and the geolocalised wire transfers (for example to ”offshore” destination).

The results on the transactions are in line with the experience and every day practice of the bank professionals, and in particular those that concern relevant cash amounts and the wire transfers. The account balance is somewhat unexpected as the current practice considers the total of positive and negative amounts, separated, rather then their difference.

On the other hand, the results concerning the ”demographic” status variables are more unexpected. In particular, the importance of the Market segment dummy variables: lower mass, top private, upper mass; indicate that all those categories are at risk, and only the ”medium” segments have a low risk. The results also indicate the need to work on the individuals for which the segment is ”Not available” . The results about the high risk from entrepreneurs and senior people are more in line with the intuition. Last, the fact that the ”consumers” variable is relevant depends on its importance, particularly for the bank.

We finally remark that our results, for both companies and indi- viduals, have been thoroughly discussed with the management of the bank, finding their agreement on the above conclusions.

ID	Variable	Relative importance
1	Account balance	1
2	Relevant amounts	0.677
3	Geo localised wire transfers	0.631
4	Lower mass market segment	0.405
5	Consumers	0.403
6	Entrepreneurs	0.377
7	Top private	0.309
8	Age greater than 65	0.257
9	Market segment NA	0.243
10	Upper mass market	0.221 height

Table 2: Final tree models - Individuals

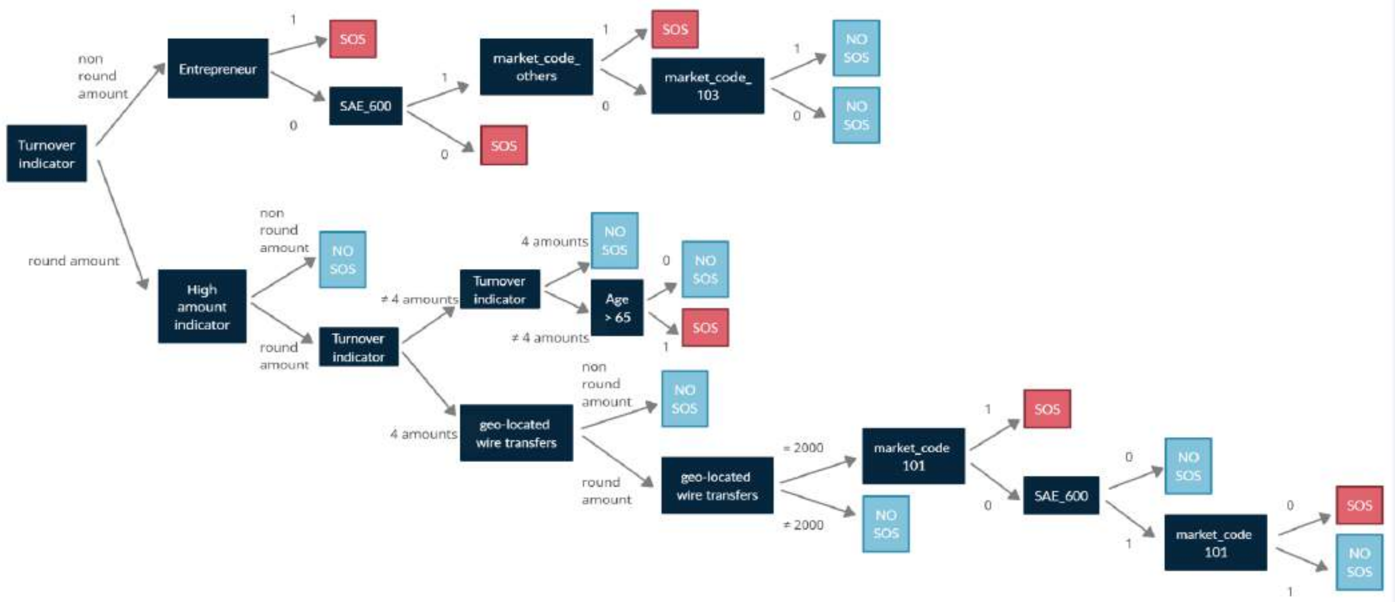

Figure 2: Final tree models - Individuals

4. Conclusions

The work in this paper shows how the "manual" activity of flagging bank transactions as suspicious money laundering activities, under constant scrutiny by supervisors, can be automatized with a save in cost and predictive accuracy. The analysis was applied on a single bank, albeit large, and it would be extremely interesting to apply to other banks, to reinforce the previous conclusions.

The application of artificial intelligence techniques reveals, once more, its potential and, in particular, the gain in predictive accuracy. This gain, however, should be balanced against negative aspects such as a more limited explainability of the results, and a possible lower robustness with respect to classical regression models.

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A remark on some extensions of the mean-variance portfolio selection models

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Abstract

Quantitative risk management techniques should prove their efficacy when financially turbulent periods are about to occur. Along the common saying "who needs an umbrella on a sunny day?", a theoretical model is really helpful when it carries the right suggestion at the proper time, that is when markets start behaving hecticly. The beginning of the third decade of the 21st century carried along a turmoil that severely affected worldwide economy and changed it, probably for good. A consequent and plausible research question could be this: which financial quantitative approaches can still be considered reliable? This article tries to partially answer this question by testing if the mean-variance selection model (Markowitz [16], [17]) and some of his refinements can provide some useful hints in terms of portfolio management.

Key Words: Mean-Variance Portfolio Selection Models; Minimum Variance Portfolios; Risk Parity Approach, Black-Litterman model.

1) Introduction and motivation

It is well known that the mean-variance portfolio selection model proposed by Markowitz ([16], [17]) is one of the stepping-stones on which modern finance relies on. It is, unfortunately, also common knowledge that, when applied to real market data, optimal mean-variance portfolios suffer of a number of drawbacks. A relevant one, the extreme sensitiveness of portfolios' weights to small variations of market data, has been clearly pinpointed, amongst many others, by Chopra and Ziemba [5]; these authors state: "small changes in the input parameters can result in large changes in composition of the optimal portfolio". Further, in their article Chopra and Ziemba show that estimation errors in expected returns can be ten times more relevant, and therefore harmful, than an estimation error in variances.

To overcome this and other issues, for instance the non-normal distribution of historically observed stock returns and the fact that some optimal portfolios have stocks with negative weights, especially when large expected returns are imposed, a relevant number of approaches have been presented. Roughly speaking, these enhancements can be divided in two groups. The first encompasses 'naïve' procedures such as the equally weighted (EW) (tested, amongst others, by DeMiguel et al. [7]), minimum variance (MV) (see, for instance, Coqueret [6]), and equal risk contribution (ERC) (a detailed explanation on this topic can be found in Roncalli [19]) ones. If the EW approach is an elementary translation of 'common sense' portfolio diversification ("don't put all your eggs in one basket"), the MV and ERC ones are based on a mathematical approach; here, optimal portfolios do not deal directly with returns, allowing to bypass, up to some extent, the negative feature identified by Chopra and Ziemba.

The second family of models exploits a range of quantitative sophisticated concepts. A key contribution was proposed by Black and Litterman [4] (BL) where the effect on optimal portfolios of market observed data (the prior) is updated in Bayesian terms introducing the so-called `views' (the posterior), i.e. opinions on the future behaviour of the whole market or on one or more stocks, expressed by the investor or a financial expert. This blending procedure between estimated parameters obtained from observed data, that are inefficient but with a low bias, and a constant estimator that, conversely, is more efficient but with a large bias, is the base for the theory of shrinkage estimators (Meucci [18]). The crucial point in this approach is the determination of the influence to be attributed to the two classes of estimators on the resulting portfolio.

Another approach deals with robustness of portfolios (see, for instance, Goldfarb and Iyengar, [10] and [11]); loosely speaking, a portfolio is robust when its weights are scarcely affected by changes in input parameters. To achieve this, actual values of the input parameters are assumed to belong to an uncertainty set whose shape allow to perform a 'robust', two-step optimization. Schöttle and Werner ([20], [21]) "robustify" the standard Markowitz model letting parameters abide in what these author name 'confidence ellipsoids'. A different vein considers inserting in the original model some additional constraints, either 'wrong' (Jagannathan and Ma [13]) or 'right' (Behr et al. [3]). For instance, DeMiguel et al. [8] show that reliable optimal portfolios are identified imposing an additional constraint on the norm of the vector of portfolio weights. Finally, Fliege and Werner [9] revisit the Markowitz model in terms of multi-objective optimization solving a bi-objective problem.

Needless to say, all these improvements come with a cost and are of difficult implementation on a practical basis. Managing a portfolio under their terms requires capabilities that could be either unfeasible or not economical. Still, the correct handling of financial portfolios is a relevant issue in risk management. Can an investor still safely trust non 'highly sophisticated' techniques? As an attempt to provide a partial answer to this question, in this article results obtained using EW, MV and ERC methodologies are discussed at first. Secondly, a BL version of these portfolios is obtained with the aim of testing how views can encompass highly stressed financial periods and if a more complex approach is worth applying.

As said above, any risk-oriented portfolio management strategy should be helpful when needed the most, that is when financial markets face a strong turbulence. A perfect example of this is year 2020, when worldwide economy has been severely tackled. The Euro Stoxx 50 stock index, whose value encompasses stocks prices of 50 European companies chosen according to their size, dropped from a value of 3793.24 on January 2nd, 2020 to the yearly minimum level of 2385.82 on March 18th, 2020[1], right after the beginning of the spread of the first wave of the infamous COVID-19 pandemic, with a loss of 26.5%.

Numerical results presented below show how supposedly risk reducing approaches might perform poorly when applied to heavily bearish financial markets. One of the reasons for this debacle can be attributed to the fact that when financial markets plummet, correlation between random returns increase, limiting or almost totally obliterating benefits of diversification.

[1] Data retrieved from https://www.wsj.com/market-data/quotes/index/XX/SX5E/historical-prices website

A similar, negative result is obtained applying the BL approach. Pessimistic views reduce the values for expected returns and inflate variances and covariance. Correlations between random returns, though, do not change, leading MV and ERC portfolios to end up with the same weights.

The structure of this article is as follows: Section 2 presents the theory and some naïve improvements of the standard portfolio selection model that will be used in Section 3 to verify the performance of the strategies under scrutiny. Section 4 eventually concludes.

2) Markowitz's model and some refinements

The original portfolio selection model developed by Markowitz encompasses n stocks whose random return $\tilde{R}_i$, $i = 1, \ldots, n$, are assumed to be fully represented in terms of the vector of expected returns $\mathbf{r} = [\bar{R_i}] \in \mathbb{R}^n$, and of the variance/covariance matrix $\Sigma = [\sigma_{i,j}] \in \mathcal{M}(n,n)$, $j = 1, \ldots, n$, where $\sigma_{i,j} = \sigma_{j,i}$ is the covariance between random returns $\tilde{R}_i$ and $\tilde{R}_j$ and $\sigma_{i,i} = \sigma_i^2$ the variance of $\tilde{R}_i$. Letting $\mathbf{x} \in \mathbb{R}^n$ be the vector portfolio weights, the optimal portfolio $\mathbf{x}^*$ according to Markowitz results solving the constrained optimization problem

$$\begin{array}{llllll} \min\limits_{\mathbf{x}} & \sigma_P^2 & = & \mathbf{x}^T\Sigma\mathbf{x} & & \\ \text{subject to} & \bar{r}_P & = & \mathbf{r}^T\mathbf{x} & = r_P & \text{expected return constraint} \\ & & & \mathbf{1}^T\mathbf{x} & = 1 & \text{budget constraint} \end{array} \qquad (1)$$

with $\mathbf{1} = [1] \in \mathbb{R}^n$ the unity vector and where the required expected portfolio return r_P is the only value an agent can choose (Szego [23]). Markowitz's model assumes that the expected return of a portfolio plays the role of a measure of its performance while its variance (or standard deviation) can be considered as a risk measure so that problem (1) seeks the 'best' (in the sense of the less risky) portfolio amongst those with the same expected return.
Additional constraints can be plugged into this model. For instance, vector $\mathbf{x}$ may only hold only non-negative values, that is $x_i \geq 0, i = 1, \ldots, n$. This imposition forbids to solve problem (1) by means of the usual Lagrange's multipliers approach. No explicit solution for the optimal portfolio is available in this and similar cases. Jagannathan and Ma introduce an upper bound x_{MAX} to weights so that $x_i \leq x_{MAX}$, $i = 1, \ldots, n$. This forces portfolio to be sufficiently diversified as no weight can be excessively large. Behr et al. substitute the non-negativity constraint with $x_i \geq x_{MIN}$, $i = 1, \ldots, n$, $x_{MIN} > 0$. Schöttle and Werner, instead, include in the variance minimization a worst-case scenario so that the problem can be stated as

$$\begin{array}{llllll} \min\limits_{\mathbf{x}} \max\limits_{(\mathbf{r},\Sigma)\in U} & \sigma_P^2 & = & \mathbf{x}^T\Sigma\mathbf{x} & & \\ \text{subject to} & \bar{r}_P & = & \mathbf{r}^T\mathbf{x} & = r_P & \text{expected return constraint} \\ & & & \mathbf{1}^T\mathbf{x} & = 1 & \text{budget constraint} \end{array}$$

where set U is "the (joint) uncertainty set for the unknown parameters $(\mathbf{r}, \Sigma)$" (see [20]) and whose shape relates to statistics confidence intervals (Meucci [18]).
Going back to problem (1), the explicit formula for the optimal portfolio weights[2], as a function of r_P is

$$\mathbf{x}^*(r_P) = \frac{(c\Sigma^{-1}\mathbf{r} - b\Sigma^{-1}\mathbf{1})r_P + (a\Sigma^{-1}\mathbf{1} - b\Sigma^{-1}\mathbf{r})}{\Delta} \qquad (2)$$

where $a = \mathbf{r}^T\Sigma^{-1}\mathbf{r}$, $b = \mathbf{r}^T\Sigma^{-1}\mathbf{1}$, $c = \mathbf{1}^T\Sigma^{-1}\mathbf{1}$, and under the assumption $\Delta = ac - b^2 \neq 0$. Further, the set of these portfolio in the $(r_P; \sigma_P^2)$ plane[3] is the quadratic function

$$\sigma^2(r_P) = \frac{cr_P^2 - 2br_P + a}{\Delta}.$$

A portfolio is efficient (according to the mean-variance dominance principle) if there is no other portfolio with the same expected return (variance) and smaller variance (larger expected return). The set of efficient portfolios is named efficient frontier. The choice of the preferred efficient portfolio is done by means of a mean-variance utility function that encompasses the agent's risk aversion.
As recalled in the Introduction, optimal portfolios are in many cases highly sensitive of changes in the input parameters. To try to overcome this drawback, a first attempt is to consider an equally weighted (EW) portfolio where $\mathbf{x}_{EW}^*(i) = 1/n$, $i = 1, \ldots, n$. Secondly, the minimum variance (MV) portfolio can be considered. Such portfolio results from a reduced version of (1) that reads

$$\begin{array}{llll} \min\limits_{\mathbf{x}} & \sigma_P^2 & = & \mathbf{x}^T\Sigma\mathbf{x} \\ \text{subject to} & & & \mathbf{1}^T\mathbf{x} = 1 \end{array}$$

and whose explicit solution in vector form is

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[2] Expression (2) contains the inverse matrix Σ^{-1} of the variance/covariance matrix Σ. Determination of Σ^{-1} requires the reciprocal of the determinant of matrix Σ. It is easy to verify that larger size variance/covariance matrices have determinants very close to 0. For instance, this determinant for the Chopra and Ziemba [5] dataset, that contains ten stocks, is $2.34 \cdot 10^{-25}$. Values of $\mathbf{x}^*$ in (2) can consequently swing greatly even with a tiny change in some input parameter.
[3] It is usual to plot portfolios in the $(\sigma_P; r_P)$ plane, where the standard deviation replaces variance. Under a geometrical point of view the set of such portfolios becomes a hyperbola rather than a parabola.

$$\mathbf{x}^*_{MV} = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}^T\Sigma^{-1}\mathbf{1}}$$

Another approach determines weights by means of the risk parity assumption (ERC): each stock in the portfolio contributes equally to its overall standard deviation $\sigma_P(x_1, \dots, x_n) = \sqrt{\mathbf{x}^T\Sigma\mathbf{x}}$. This result is obtained exploiting Euler's homogeneous functions theorem[4] that allows to decompose function $\sigma_P(\mathbf{x})$, homogeneous of degree 1, as follows

$$\sigma_P(\mathbf{x}) = \sum_{i=1}^{n} x_i \cdot \frac{\partial}{\partial x_i}\sigma_P(\mathbf{x}).$$

Marginal contributions are expressed as

$$\frac{\partial}{\partial x_i}\sigma_P(\mathbf{x}) = \frac{\sum_{k=1}^{n}\sigma_{i,k}\cdot x_k}{\mathbf{x}^T\Sigma\mathbf{x}}$$

while product $x_i \cdot \frac{\partial}{\partial x_i}\sigma_P(\mathbf{x})$ stands for the risk contribution of the i −th stock. Imposing an equal contribution to the overall risk by each stock, that is,

$$x_i \cdot \frac{\partial}{\partial x_i}\sigma_P(\mathbf{x}) = x_j \cdot \frac{\partial}{\partial x_j}\sigma_P(\mathbf{x}), \quad \forall i, j = 1, \dots, n, i \neq j$$

along with the usual budget constraint $\mathbf{1}^T\mathbf{x} = 1$ yields portfolio $\mathbf{x}^*_{ERP}$.
Unlike the EW and MV cases, there is no explicit expression for this portfolio when $n \geq 3$; its weights must be numerically determined by means of some constrained minimization algorithm[5]. An approach is by solving the optimization problem (see Maillard et al. [14])

$$\arg\min_{\mathbf{x}} \sum_{i=1}^{n}\left(\frac{\sqrt{\mathbf{x}^T\Sigma\mathbf{x}}}{n} - x_i \cdot \frac{\sum_{k=1}^{n}\sigma_{i,k}\cdot x_i}{\sqrt{\mathbf{x}^T\Sigma\mathbf{x}}}\right)$$

In the numerical part of this article, portfolio weights have been obtained exploiting Matlab's website on-line resources[6].
An important departure from the above models is due to Black and Litterman (BL) [4]. Their approach considers a 'prior', that is a set of information merely subsumed from historical market data. A key point here is the reference portfolio, that, in the original BL setting, is the CAPM's (Sharpe [22]) market one. Its weights are obtained by means of "reverse optimization"[7] that considers also a risk aversion parameter δ. Investors' sentiments and knowledge (the 'posterior') are introduced by means of k 'views' that can be either absolute or relative. An absolute view is a claim made on the future behaviour of a specific stock. A relative view allows, instead, to include an opinion on the relative performance on two or more stocks. The matrix that identifies such views is denoted by $P \in \boldsymbol{\mathcal{M}}(k, n)$ while $Q \in \mathbb{R}^k$ is the view vector. Each row in P introduces a view whose numerical claim is an element in Q. Vector $\Pi \in \mathbb{R}^n$ is the reference portfolio. Along with Bayesian decision theory, errors in judgement should be attached to predictions. The numerical measurements of these quantities are expressed in terms of variances of the views and contained into a diagonal matrix $\Omega = [\omega_{u,v}] \in \boldsymbol{\mathcal{M}}(k, k),\ u, v = 1, \dots, k$ where $\omega_{u,v} = 0$ whenever $u \neq v$. A way to determine Ω is proposed by Meucci [18]:

$$\Omega = \left(\frac{1}{c} - 1\right)P\Sigma P' \qquad (3)$$

where $c \in (0; 1)$ so that if $c \to 0$ views are not deemed informative while when $c \to 1$ views are entirely trusted. A final parameter needed is τ, whose aim is to shift the model's focus to either market portfolios or views. All these pieces of information lead to a view-corrected vector of expected returns (Meucci [18])

$$\mathbf{r}_{\mathrm{BL}} = \mathbf{r} - \Sigma P'(P\Sigma P' + \Omega)^{-1}(Q - P\mathbf{r}) \qquad (4)$$

and a view corrected variance-covariance matrix

$$\Sigma_{BL} = \Sigma - \Sigma P'(P\Sigma P' + \Omega)^{-1}P\Sigma. \qquad (5)$$

[4] Let $f(\mathbf{x})\colon \mathbb{R}^n_+ \to \mathbb{R}$ be a C^1 homogeneous function of degree γ. Then, for all $\mathbf{x}$

$$x_1 \cdot \frac{\partial}{\partial x_1}f(\mathbf{x}) + \dots x_n \cdot \frac{\partial}{\partial x_n}f(\mathbf{x}) = \gamma \cdot f(\mathbf{x})$$

[5] In Appendix, a brief discussion of the $n = 2$ case, that has an analytic solution, is presented.
[6] Refer to https://it.mathworks.com/matlabcentral/answers/278745-risk-parity-equal-risk-contribution-optimization, where MATLAB's function fmincon is exploited.
[7] For the full mathematical description of the BL model, refer to (Idzorek [12]).

Having concluded the theoretical part and armed with all required formulas, the rest of this article tackles a real-market application and analyses its results.

3) Data and numerical results

In order to test the claim this article evaluating, historical weekly prices of five stocks[8] (ENI, E.ON, Generali, SAP, and Volkswagen) have been considered. This choice has no specific reason but to encompass companies whose random returns can be considered sufficiently diversified. Correlations between random returns in Table 3a confirms this and hints that portfolios containing these stocks should allow for some degree of diversification.
Overall data ranging from the beginning of 2016 to the end of 2020, for a total of 260 weekly log-returns, have been divided in two subgroups: the first 208 returns (years 2016-2019) are used to determine the historical vector of expected returns $\mathbf{r}$ (Table 1, second column), the variance/covariance matrix Σ (Table 2a), and the correlation matrix (Table 3a). These are the input required to determine portfolio weights in the cases described before. Variance-covariance (Table 2b) and correlation (Table 3b) matrices come from the remaining 52 observations (year 2020). Table 1 also contains additional descriptive statistics; as a remark, excess kurtosis for all stocks is positive, suggesting that, as usual with stocks, historical returns show a leptokurtic (i.e. fat-tail) behaviour for which 'rare' events occur with a frequency unattainable to phenomena described with the normal distribution.

Table 1a – Descriptive Statistics for 2016-2019 weekly log-returns of companies E.On, ENI, Generali, SAP, and Volkswagen. (Total number of observations: 208)

stock	Mean ($\mathbf{r}_{2015-2019}$)	median	min	max	st. dev.	skewness	exc. Kurtosis
E.ON	0.0022	-0.0007	-0.1517	0.1161	0.0366	-0.1862	1.6377
ENI	0.0016	0.0032	-0.0731	0.1127	0.0291	-0.0097	0.6887
GEN	0.002	0.004	-0.1192	0.1301	0.0329	-0.1077	2.3352
SAP	0.0028	0.0049	-0.0778	0.1292	0.028	0.3308	2.1864
VW	0.0019	0.0005	-0.0779	0.1248	0.0343	0.391	0.5606

Table 1b – Mean of weekly log-returns for companies under scrutiny for year 2020 - (a): Jan 1st-Jun 30th; (b): Jan 1st-Dec 31st (Total number of observations: 52)

stock	6-month return (a)	12-month return (b)
E.ON	0.2323	-0.00613
ENI	-0.82225	-0.41717
GEN	-0.50433	-0.22083
SAP	0.15215	-0.09307
VW	-0.35566	0.00618

Table 2a – Variance/Covariance matrix ($\Sigma_{2015-2019}$) for observed weekly log-returns (2016-1019)

	E.ON	ENI	GEN	SAP	VW
E.ON	0.00134				
ENI	0.00045	0.00085			
GEN	0.00029	0.00044	0.00108		
SAP	0.00026	0.00027	0.00032	0.00078	
VW	0.00041	0.00038	0.00044	0.00038	0.00118

Table 2b – Variance/Covariance matrix for observed weekly log-returns (2020)

	E.ON	ENI	GEN	SAP	VW
E.ON	0.00221				
ENI	0.00274	0.00677			
GEN	0.00225	0.00414	0.00304		
SAP	0.00202	0.00289	0.00246	0.00421	
VW	0.00241	0.00389	0.00336	0.00297	0.00436

Table 3a – Correlation matrix for observed weekly log-returns (2016-2019)

	E.ON	ENI	GEN	SAP	VW
E.ON	1				
ENI	0.42174	1			
GEN	0.23997	0.46369	1		
SAP	0.2505	0.33118	0.34307	1	
VW	0.32716	0.37912	0.39445	0.392998	1

A comparison between values in Tables 2a, 2b, 3a, and 3b clearly displays that, due to the COVID-19 induced financial crisis, all variances, covariances, and correlations in year 2020 substantially increase. This means that portfolios whose composition has been obtained using historical data from 2016 to 2019 (Table 4) might suffer of severe misspecification if applied to 2020 data, resulting in large, unexpected risk levels.

[8] Data (adjusted closing prices) retrieved from https://it.finance.yahoo.com/

Table 3b – Correlation matrix for observed weekly log-returns (2020)

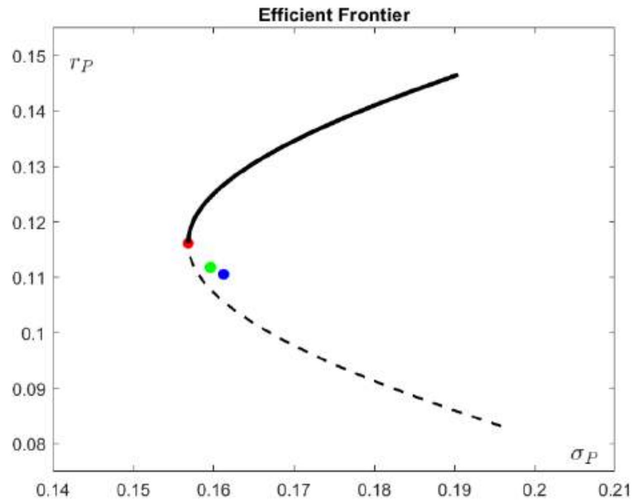
	E.ON	ENI	GEN	SAP	VW
E.ON	1				
ENI	0.70728	1			
GEN	0.81096	0.85554	1		
SAP	0.66282	0.54573	0.64565	1	
VW	0.77441	0.72173	0.86674	0.69235	1

Table 4 – Portfolio weights for the equally weighted (second column), minimum variance (third column) and equally risk contribution (fourth column) portfolios obtained using the 2016-2019 period data

	EW	MV	ERC
E.ON	0.2	0.1376	0.1847
ENI	0.2	0.2433	0.206
GEN	0.2	0.1534	0.193
SAP	0.2	0.3656	0.2354
VW	0.2	0.1003	0.1809

A first remark that can be drawn looking at weights in Table 4 is that, according to the peculiar choice of stocks made here, the EW composition acts as a ‘continental divide’ between stocks whose relative quantities are smaller (larger) than 0.2. If the weight of a stock is less than the EW one in the MV portfolio it does not trespass this threshold in the ERC portfolio as well. A possible explanation to this fact is that the minimum variance and equal risk contribution approaches treat risky and less risky stocks alike, assigning them smaller or larger weights.
Figure 1 represents the efficient frontier (continuous plot) in the usual standard deviation/expected return two-dimensional plane; the red point pinpoints the MV portfolio, the blue and green ones, respectively, the EW and ERC portfolios. For ease of display, returns and standard deviations have been transformed on a yearly basis.

Figure 1 – efficient frontier (black continuous curve) in the (σ_P, r_P) plane with dots depicting portfolios: EW (blue dot), MV (red dot) and ERC (green dot). Data have been annualized.



It is interesting to notice (Table 5) that MV portfolio dominates, according to the mean-variance criterion, the ERC one and that EW portfolio is dominated by the other two. This result seems acceptable as the latter portfolio is determined without trying to actively manage its risk.

Table 5 – realized yearly expected returns and standard deviations for portfolios under scrutiny (2016-2019)

	expected return	standard deviation
MV	0.1161	0.1568
EW	0.1105	0.1612
ERC	0.1118	0.1596

Efficient portfolios and their expected returns with the same standard deviation as the EW and ERC ones are reported in Table 6. Even if only two efficient portfolios are displayed, it seems evident that both assign a large weight to SAP stock. This result might derive to the fact that SAP Sharpe’s ratio is larger than the other ones. Even if this is a theoretically correct choice, such feature could deliver portfolios that are not well-balanced as they are exposed to any negative changes in the performance of SAP’s stock.

Table 6 – weights and expected returns of efficient portfolios with the same standard deviation of the EW and ERC ones (annualized data).

	$\sigma_P = 0.1612$ (EW)	$\sigma_P = 0.1596$ (ERC)
E.ON	0.17024	0.16351
ENI	0.09708	0.12719
GEN	0.15376	0.15368
SAP	0.5278	0.49438
VW	0.05112	0.06125
r_P	0.1266	0.12445

The first result in the empirical analysis deals with the performance of 'historically' determined (i.e., based on 2016-2019 data) EW, MV, and ERC portfolios when applied to year 2020 values. This is achieved by computing the realized yearly return[9] using data for time interval Jan 1st-June 30th, 2020 (interval a) and the realized yearly return and standard deviation for time interval Jan 1st-Dec 31st, 2020 (interval b). Period Jan 1st – Mar 31st, 2020 cannot be unfortunately considered as its yearly log-returns show an abnormal behaviour as some returns are so negative that their transformation on an yearly basis makes them with no sensible financial meaning. Table 7 displays these values.

Table 7: realized yearly returns and realized 12-month standard deviations for EW, MV, and ERC portfolios in 2020. Due to the negative dynamics of stock prices in 2020, losses occur in all cases.

portfolios	6-month return (interval a)	12-month return (interval b)	12-month st dev (interval b)
EW	-0.2596	-0.1462	0.40605
MV	-0.2255	-0.1696	0.41346
ERC	-0.2524	-0.1505	0.40687

A comparison between Tables 5 and 7 further shows how riskier and poorly performing portfolios made of the chosen stocks ended up being in 2020.
Another benchmark is displayed in Table 8 where portfolio weights for the MV and ERC cases obtained using Table 2b data (year 2020 variance/covariance matrix) are:

Table 8 – Portfolio weights for the minimum variance (second column) and equally risk contribution (third column) portfolios obtained using variance/covariance matrix in Table 8.

	MV	ERC
E.ON	0.9532	0.6589
ENI	-0.2569	-1.2909
GEN	0.4165	0.7799
SAP	0.1237	0.4065
VW	-0.2364	0.4455

These weights produce abnormal portfolios with both short selling and large fractions invested in some stocks, features that can hardly be associated to proper risk reduction.
The second analysis performed relies on the Black-Litterman version of EW, MV, and ERC portfolios. In the BL framework the starting portfolio is the implied equilibrium one, out of which excess equilibrium returns are obtained. Here, partially departing from the underlying theory, such returns are the historical ones (Table 1a, second column). Further, as risk-less rates during period 2015-2020 have been very close to zero (or even negative), excess returns can be set equal to realized ones. Views are assumed to be pessimistic. In a first instance, all expected returns are obtained subtracting to each historical expected return a portion of the respective standard deviation. Matrix P is

$$P = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & -1 \end{bmatrix}.$$

The single, negative value in each of its rows translates the absolute view made on each stock: to the expected return of the i −th stock (i −th element of the i −th row) is assigned the i −th element of view vector

$$Q = \begin{bmatrix} 0.00223 - 0.5 \cdot 0.03661 \\ 0.0016 - 0.5 \cdot 0.02913 \\ 0.00204 - 0.5 \cdot 0.03285 \\ 0.00282 - 0.5 \cdot 0.02797 \\ 0.00194 - 0.5 \cdot 0.03432 \end{bmatrix} = \begin{bmatrix} -0.01597 \\ -0.012965 \\ -0.014386 \\ -0.011163 \\ -0.015221 \end{bmatrix} \qquad (6)$$

[9] For the six-month interval, the number of available observations is deemed to be not sufficient to be safely trusted as standard deviations might end up with misleading results.

where 50% of the 2015-2019 standard deviation is assumed to be large enough to penalize historical expected returns. Diagonal matrix Ω is obtained according to (3), letting $c = 0.25$ (views are mildly informative) and $c = 0.75$ (views display a large degree of trustworthiness). Posterior estimates for the expected returns are, according to (4)

$$\bar{\mathbf{r}}_{BL} = \begin{bmatrix} -0.00108 \\ -0.00124 \\ -0.00105 \\ 0.00073 \\ -0.00138 \end{bmatrix} \text{ when } c = 0.25 \text{ and } \bar{\mathbf{r}}_{BL} = \begin{bmatrix} -0.0079 \\ -0.00692 \\ -0.00722 \\ -0.00344 \\ -0.00802 \end{bmatrix} \text{ when } c = 0.75.$$

Needless to say, all estimates but the one for SAP in the first case, are smaller than historical returns. Posterior estimates of the variance-covariance matrices (see formula (5)) are

$$\Sigma_{\mathrm{BL}} = \begin{bmatrix} 0.00168 & & & & \\ 0.00056 & 0.00106 & & & \\ 0.00036 & 0.00055 & 0.00135 & & \\ 0.00032 & 0.00034 & 0.00039 & 0.00098 & \\ 0.00051 & 0.00047 & 0.00056 & 0.00047 & 0.0015 \end{bmatrix} (c_1 = 0.25),$$

$$\text{and } \Sigma_{BL} = \begin{bmatrix} 0.00235 & & & & \\ 0.00079 & 0.00149 & & & \\ 0.00051 & 0.00078 & 0.00189 & & \\ 0.00045 & 0.00047 & 0.00055 & 0.00137 & \\ 0.00072 & 0.00066 & 0.00078 & 0.00066 & 0.00206 \end{bmatrix} (c_1 = 0.75).$$

Using these latter inputs, it results that MV and ERC portfolios are the same obtained above. This result is due to the fact that both matrices embed larger variances and covariances but correlations are the same. This particular instance shows that when all stocks share the same view, the Black-Litterman model correctly changes expected return vectors and variance-covariance matrices but is unable to adjust correlations.

Secondly, absolute views are provided only for a stock at a time. Matrix P shrinks to a row vector with all null elements but one, equal to -1, its position in P identifying which stock the views relates to. The view value is corresponding value in Q. If, for instance, the absolute negative view is about E.ON, the first stock in matrix Q (see (6)), posterior estimates for the expected returns are now

$$\bar{\mathbf{r}}_{BL} = \begin{bmatrix} -0.00108 \\ 0.000455 \\ 0.001305 \\ 0.002167 \\ 0.000894 \end{bmatrix} \text{ when } c_1 = 0.25 \text{ and } \bar{\mathbf{r}}_{BL} = \begin{bmatrix} -0.0079 \\ -0.00183 \\ -0.00016 \\ 0.00086 \\ -0.0012 \end{bmatrix} \text{ when } c_1 = 0.75$$

while the variance-covariance matrices here read

$$\Sigma_{\mathrm{BL}} = \begin{bmatrix} 0.00168 & & & & \\ 0.00056 & 0.00089 & & & \\ 0.00036 & 0.00047 & 0.00109 & & \\ 0.00032 & 0.00029 & 0.00033 & 0.00079 & \\ 0.00051 & 0.00041 & 0.00047 & 0.0004 & 0.00121 \end{bmatrix} (c = 0.25),$$

$$\text{and } \Sigma_{BL} = \begin{bmatrix} 0.00235 & & & & \\ 0.00079 & 0.00096 & & & \\ 0.00051 & 0.00052 & 0.00112 & & \\ 0.00045 & 0.00033 & 0.00036 & 0.00082 & \\ 0.00072 & 0.00048 & 0.00051 & 0.00044 & 0.00127 \end{bmatrix} (c = 0.75).$$

These results deserve some comments. Expected returns, variances and covariances of stocks unaffected by the view improve, in the sense that the BL adjustment leads to larger expected returns and smaller variances and covariances while data for E.ON remain unchanged. Remarkably, an absolute view does not directly affect the stock its posterior estimates but estimates of the other stock involved in the analysis. MV and ERC portfolios are

Table 9 – Portfolio weights for minimum variance (second and third columns) and equally risk contribution (fourth and fifth columns) portfolios obtained using variance-covariance matrices encompassing a negative, absolute view on E.ON

	MV ($c = 0.25$)	MV ($c = 0.75$)	ERC ($c = 0.25$)	ERC ($c = 0.75$)
E.ON	0.0721	-0.0161	-0.6623	-0.5802
ENI	0.2617	0.2866	0.485	0.4682
GEN	0.165	0.1807	0.3536	0.3351
SAP	0.3933	0.4307	0.4483	0.4253
VW	0.1079	0.1181	0.3754	0.357

Weights in Table 9 reflect the absolute and pessimistic view attached to E.ON stock. Its contribution to the optimal portfolio decreases in all cases. On top of this, in three instances the optimal portfolios carry negative weights of E.ON stock. The level of its risk is deemed so large when compared to the ones of the other stocks that an advantage in short selling the stock appears.

Finally, Tables 10a and 10b display the view-adjusted correlation matrices.

Table 10a – Correlation matrix for view-adjusted variance-covariance matrix $(c = 0.25)$

	E.ON	ENI	GEN	SAP	VW
E.ON	1				
ENI	0.5793	1			
GEN	0.46406	0.72662	1		
SAP	0.43745	0.57332	0.54819	1	
VW	0.55384	0.68308	0.65305	0.70684	1

Table 10b – Correlation matrix for view-adjusted variance-covariance matrix $(c = 0.75)$

	E.ON	ENI	GEN	SAP	VW
E.ON	1				
ENI	0.5793	1			
GEN	0.46406	0.73273	1		
SAP	0.43745	0.58961	0.5628	1	
VW	0.55384	0.70831	0.67381	0.72985	1

It is worth stressing that even if the view regards only one stock, correlations between the other stocks end up being affected by the view itself.
Similar findings occur when applying an absolute view to one of the remaining stocks. For sake of paucity numerical results have been omitted.

4) Conclusions

Since finance started being, in the second half of the twentieth century, a topic of its own, risk management has strived to tackle real market problems under both a theoretical and a practical point of view. Among the tools that can be used in this context, mean-variance portfolio analysis has been, by far, the most studied and investigated. Unfortunately, this methodology (at least in the range this article has dealt with) proves to be unsuccessful when markets are hit by crashes and severe turbulences. This article has also shown that the Black-Litterman approach, is uncapable of modifying correlations between random returns when views are absolute and share the same structure. This might mean that the application of the BL methodology, that confirms its importance when applied to the forecasted behaviour of single stocks, needs to be finely tuned when an overall drop in stock prices is expected. Even if Markowitz's model provides some useful insights and the basis for more sophisticated approaches, up to the extent of stocks considered in this contribution its solid market application appears to be debatable.
It might be interesting, and left for subsequent research, to perform a similar analysis where more recent risk measures, such as Value-At-Risk and Expected Shortfall (Artzner et al. [1], Bagnato et al. [2]) replace variance. With tools capable of detecting tail and non-normal shapes of risk an analysis similar to the one performed here might result with a more positive ending.

Appendix

In order to provide an intuition of the structure of these weights, consider case $n = 2$ where an explicit expression for $\mathbf{x}_{ERP}^*$ exists. Starting from the risk contributions of stocks 1 and 2

$$\frac{x_1^2\sigma_1^2 + x_1x_2\sigma_{1,2}}{x_1^2\sigma_1^2 + 2x_1x_2\sigma_{1,2} + x_2^2\sigma_2^2}, \qquad \frac{x_1x_2\sigma_{1,2} + x_2^2\sigma_2^2}{x_1^2\sigma_1^2 + 2x_1x_2\sigma_{1,2} + x_2^2\sigma_2^2}$$

and recalling that $x_1+x_2 = 1$, equating the two above quantities yields

$$\mathbf{x}_{ERC}^* = \left[\frac{\sigma_2}{\sigma_1+\sigma_2}, \qquad \frac{\sigma_1}{\sigma_1+\sigma_2}\right]$$

It is easy to verify that in this case portfolio weight of the first (second) stock is linearly dependant on standard deviation of the second (first) stock and that these weights do not depend on the correlation between random returns of the two stocks (Maillard et al. [15]).

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Covid-19 crisis and its impacts on the economic and financial sector

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Abstract

The World Bank data confirm that the recovery scenario will be different depending on the type of nation, the fundamentals of its economy, etc.. The Bank of Italy expects a growth of more than 4% for Italy at the end of 2021.
The Italian banking system has shown great flexibility in dealing with the coronavirus emergency, taking a completely different form from the last in 2008 recession, when credit institutions were part of the problem.
With their new social role, today in fact they are leading players. The health of the banking sector has also changed compared to 2008, with a stronger capital position, underlying the substantial resilience of the ecosystem and a more advanced expertise in NPL management.
The role of the banks operating in Italy has been and will be to support firms, households and the growth of the economy with the sound and prudent distribution of credit, the offer of modern and efficient payment services thanks also to new technologies, business advice to companies for the development and internationalization.
A clear evolution is opening up for banks in post-Covid towards digital business with a growing commitment in terms of investments in information technology.

Introduction

The Covid-19 pandemic has had extremely serious human, social and economic effects. The spread of the virus has affected the entire economy and the economic effects have appeared to different extents across sectors and geographic areas, reflecting the severity of the pandemic at local level and the economic policy responses.
The vaccination campaign and the easing of restrictions in 2021 are paving the way for economic recovery. In Italy, vaccine delivery is accelerating after a slow start hindered mainly by supply and distribution problems and uncertainty about the side effects.
The goal of the Italian government was to vaccinate 80% of the population by September 2021 and it has now been achieved
Rising vaccination rates and easing restrictions in Italy will drive economic recovery.
There remains substantial uncertainty about the unfolding of the virus with the evolution of new, more contagious and lethal variants that are more resistant to existing vaccines, unless effective vaccinations become widespread everywhere. New infections would require new containment measures, with economic costs linked to lower confidence thus lower spending.
The financial sector has so far proved to be resilient to the impact of the Covid-19 crisis. Although financial risks for credit institutions have increased, they have continued to support the economy by providing new loans to businesses and households (net of the moratoriums that have been granted).
The growth prospects of banks in the European Union for 2021 are linked to credit quality problems and weakened profitability prospects. Banks entered the pandemic with huge reserves of capital and liquidity, which should help them overcome the Covid-19 crisis, at least for now. The effect of the macroeconomic shock induced by the pandemic on companies' balance sheets will force banks to accelerate their consolidation.
Given regulatory pressure and the high cost of capital of riskier assets, many banks have nowadays had to reduce the size of their market activities, or even stop those that absorbed too much capital. Regulatory changes, external conditions, modest economic growth, a low interest rate environment and a lack of cost structure optimization all raise serious questions about the business model.
Many of these factors are changing for the better, which would tend to make the banking sector more attractive than it has been in the past few years.
An increasingly marked polarization will take place between large banks able to invest and more agile banks able to adapt to the digital world.
According to the new Sustainable Finance Report of the Foundation for Subsidiarity, almost 10,000 bank branches have been closed in Italy in ten years: from 34,036 at the beginning of 2010 to 24,312 at the beginning of 2020, about 30% less. Digital, competition and the challenge of sustainability are revolutionizing banks and customer relations.
This paper proposes a few reflections on the interventions implemented by the European institutions to address the economic crisis generated by the Covid 19 pandemic and on the possible implications on the banking system in the post-crisis period.
In the following paragraphs, the main aspects of the economic-financial crisis are depicted and analyzed.

1. Economic and financial situation pre-Covid crisis in Italy and in the euro area

Already in 2019, before the outbreak of the pandemic that profoundly changed the growth prospects of the economy, there had been a slight reduction in the growth of the global economy (2.9% compared to 3.6% recorded the previous year- Source: ECB) due to the slowdown in international trade, the weakness of some industrial sectors and concerns about the way the United Kingdom would leave the European Union (Brexit).
The GDP of the euro area at the end of 2019 had grown by only 1.2%, with a slowdown compared to the previous year in all the main economies (Table 1). Within the Eurozone, Italy had recorded a GDP of 0.3%, a decline compared to the previous year (0.8% recorded in 2018) and the worst figure, if compared to Germany, France and Spain.
Starting from the end of 2015, Italian banks have raised the quality of assets as a result of more prudent credit risk management policies and thanks also to the substantial reduction in the amount of non-performing loans (NPLs).
All this has led to a significant decline in impaired loans recorded in the balance sheets of banks which at the end of 2019, net of value adjustments, amounted to approximately € 70 billion (Figure 1).

[1] The thoughts and information expressed herein are solely those of the author and do not in any way bind the institution he belongs to.

Table 1 – GDP Euro area

GDP in the main euro area countries (1)

(percentage variation on previous period)

PAESI	2017	2018	2019	2019				2020
				1° trim.	2° trim.	3° trim.	4° trim.	1° trim.
Area dell'euro (2)	2,5	1,9	1,2	0,5	0,1	0,3	0,1	-3,8
Francia	2,3	1,7	1,3	0,4	0,3	0,3	-0,1	-5,8
Germania	2,5	1,5	0,6	0,5	-0,2	0,3	-0,1	-2,2
Italia	1,7	0,8	0,3	0,2	0,1	0,1	-0,3	-4,7
Spagna	2,9	2,4	2,0	0,6	0,4	0,4	0,4	-5,2

Source: Bank of Italy
From top to bottom: euro area (2), France, Germany, Italy, Spain.
From left to right: 2017, 2018, 2019, 1Q2019, 2Q2019, 3Q2019, 4Q2019, 1Q2020

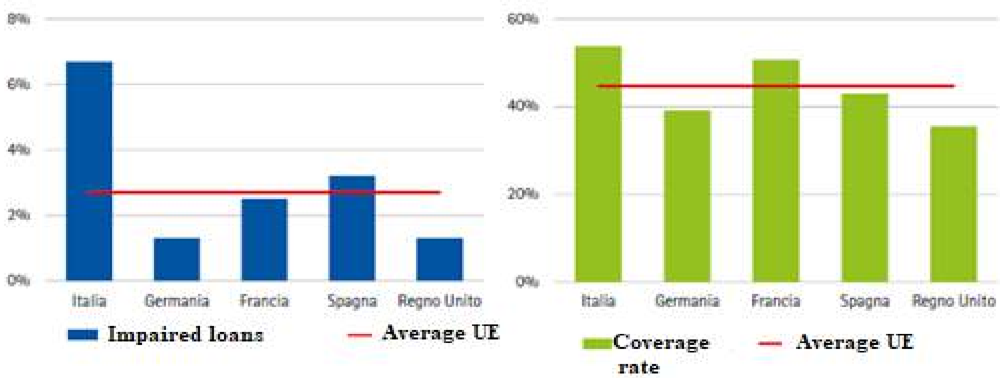
(1) Concatenated values. Quarterly series are seasonally adjusted and corrected for working days
(2) The euro area aggregate refers to the composition of 19 countries.

In comparison with European institutions, the Italian banking system at the end of 2019 (Figure 2) recorded a higher incidence of impaired loans on the total, equal to 6.7% (gross of adjustments) compared to a European average of 2.7%. The coverage rate of NPLs was equal to approximately 54%, significantly higher than the European average, close to 45%.

Figure 1- Non-performing loans and better-quality capital

Source: Bank of Italy
Non-performing loans (right-hand scale)
Better quality capital

Figure 2 - Credit quality of the biggest European banks at the end of 2019

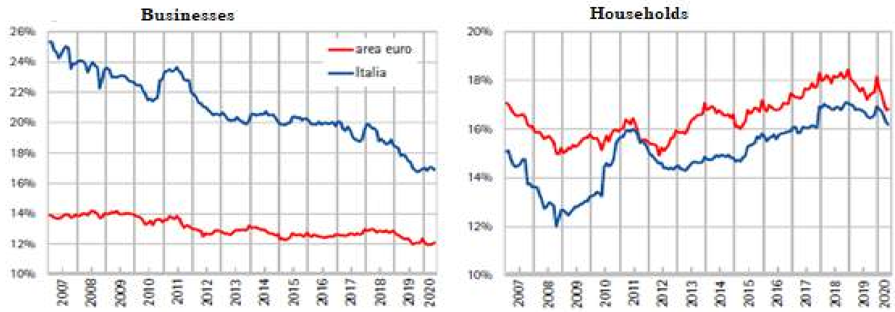


Source: CONSOB based on EBA data
From left to right: Italy, Germany, France, Spain, UK.
Blue histograms: incidence of deteriorated loans on total loans, green histograms: coverage ratio, red line indicates the EU average

Starting from 2007 (Figure 3), Italy recorded a significant decrease in the weight of bank credit to businesses on the assets of banks. At the end of 2019, the incidence of loans to businesses on the total assets of Italian banks (about 17%) remained significantly higher than the European average (12%). On the other hand, the gap is less relevant with regard to loans to households.
As evidenced from the figure below, Italian businesses are the most dependent on bank credit in Europe.

In this context, as highlighted by the ECB which has always kept encouraging Italy, it is necessary to consistently promote the use of alternative instruments to bank credit (mini bonds, crowfunding, private debt funds, pir, eltif, etc.) in order to reduce the credit risk for banks. The new rules already in force such as calendar provisioning or the new definition of default aim, in fact, to discourage traditional credit, in the same way as the new requirements for the calculation of RWA imposed by Basel III (IV).

Figure 3 - Weight of bank loans to businesses and households on total assets

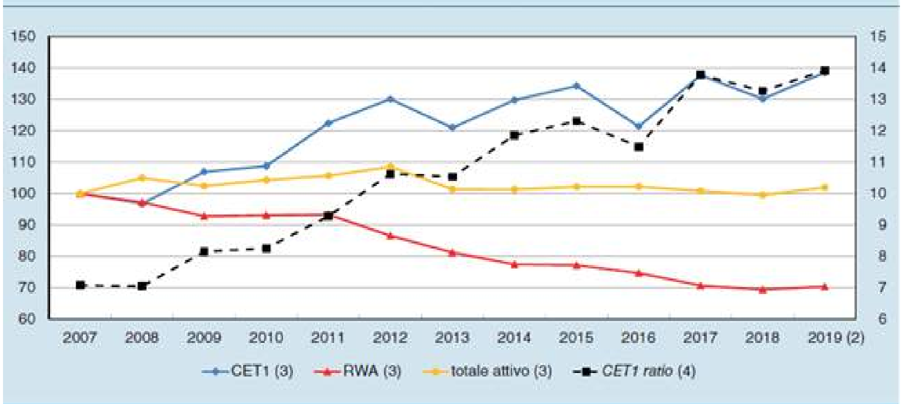


Source: CONSOB based on ECB data
Businesses on the left-hand side and households on the right-hand side

In 2019, the profitability of Italian banks has continued to decline compared to the previous year, mainly due to the reduction in the interest margin. The return on equity (ROE) recorded was 5.0%, net of extraordinary components (Source Bank of Italy), compared to 5.7% recorded in 2018.
For significant banks, the ROE stood at 4.9% (5.8% on average for the main European groups). For the less significant ones, on the other hand, the ROE was equal to 6.5%. Banks that mainly carry out financing activities to households and businesses achieved a very low ROE on average, while the result of banks specialized in investment services and in particular segments of the credit market was higher.
In 2019, the capital strengthening of Italian banks resumed after it had stopped in 2018. In this context, the CET1 Ratio, the ratio between the best quality capital (common equity tier 1, CET1) and risk-weighted assets (RWA), stood at 13.9% (Figure 4), recording an increase of over 60 basis points higher than at the end of 2018.
The improvement is largely due to the increase in CET1, which benefited above all from the positive economic result of the year and the revaluation of assets measured at fair value.

Figure 4 - Evolution of CET1 ratio and RWA

Evolution of better quality capital and risk-weighted assets of Italian banks and banking groups (1*)(percentage values*)



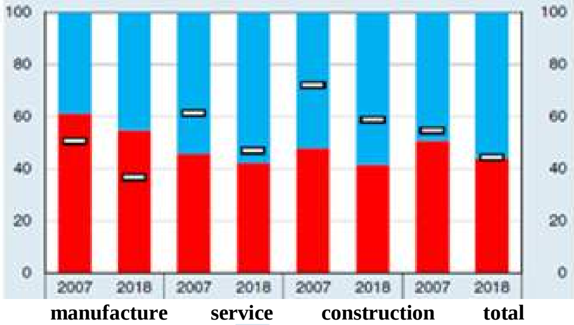
Source: Bank of Italy
Blue line: CET1 (3), red line: RWA (3), yellow line: total assets (3), black dotted line: CET1 (4).

(1) Better quality capital means *core tier 1* until December 2013 and, from March 2014, CET1. To define the aggregates, compare the item *Banks and banking groups*: *profitability and capital adequacy* in the *Methodological Notes* section of the Appendix. - (2) Provisional data. – (3) Index: 2007 = 100. – (4) Right-hand scale.

The current crisis would be more painful without the improvements in banks strength that has been ongoing since 2016.
A "pre-crisis" situation could still be observed at the end of 2020 since the effects of the economic difficulties are typically reflected on bank balance sheets with a certain delay, but above all because, in the face of the Covid crisis, governmental and sectoral measures have been adopted with the goal of preventing temporary difficulties from translating into insolvencies.
The extent of such effects will depend on the duration of the recession and on the speed of recovery. The measures adopted by the supervisory authorities aim to contain the consequences of the pandemic on banks' ability to finance the economy and to avoid pro-cyclical effects. Since February 2020, companies have faced the pandemic crisis altogether with a more balanced financial structure than they had on the eve of the double recession of 2008-2013. Financial leverage (measured as the ratio between financial payables and the sum of such payables and shareholders' equity) was found to be approximately 10% lower; the incidence of short-term debts on the total of financial debts fell by 7.00% (Source: Bank of Italy)[2]. The decrease in overall debt and the lengthening of maturities have affected all sectors of activity (Figure 5).

[2] See Bank of Italy, Report on financial stability no. 1/2020

Figure 5 - Financial leverage and breakdown of payables by due date



short-term financial debts long-term financial debts leverage

Source: Cerved From the left-hand side: manufacture, services, construction and total.
Red: short-term financial debt, blue: long-term financial debt, the white dash indicates the leverage.

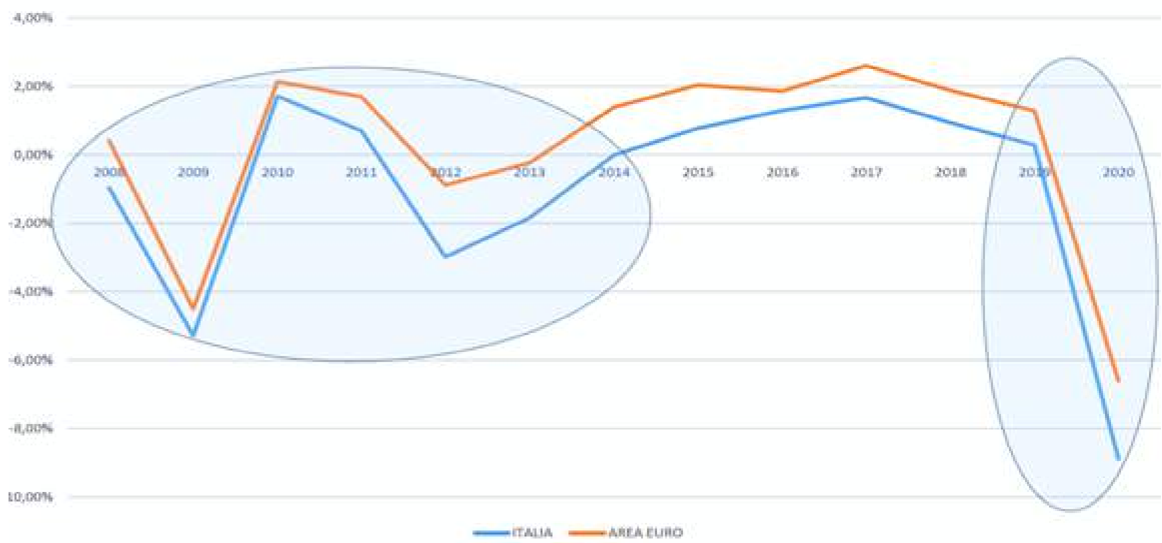
At the end of 2019 (Source: Bank of Italy) the profitability of companies had reached high levels. The increased solidity of balance sheets and the low interest rates have favored the decline in the deterioration rate of loans to 1.9%, a level lower than the values observed in 2007 (2.6%). The debt ratio of vulnerable companies[3] was estimated at 28% (compared to 44% in 2007).

2. Impacts of the crisis on the economic and financial system in Italy and in the European Union and measures adopted by Governments

The health emergency in which the world has plunged since February 2020 due to the spread of Covid has generated significant economic implications, both in terms of nature and intensity.

At the onset of the COVID-19 pandemic, rapidly evolving social restrictions have been put in place, macroeconomic uncertainty was at an all-time high as well as the pronounced deterioration in the climate of business and consumer confidence. The European Union has faced a crisis of unprecedented magnitude and contours.
The spread of the pandemic resulted in an exogenous and symmetrical shock that hit the demand side and the supply side simultaneously, within the economies involved.
The timing and intensity of the recovery will depend on several factors**:** the duration of the contamination, the evolution of the global economy, the effects on business confidence and investment decisions, the effectiveness of the economic policies that were introduced and the strategies adopted.
The latest data observed in Europe in 2020 confirm that the economic effects have been significant.
In the Euro area and in the European Union, GDP in 2020 (Figure 6) revealed a contraction of -6.8% and -6.4% (Source Eurostat), while in Italy the gross domestic product shrank by -8.9% (Source Istat).

Figure 6 - Evolution of the GDP in the Euro / Italy area



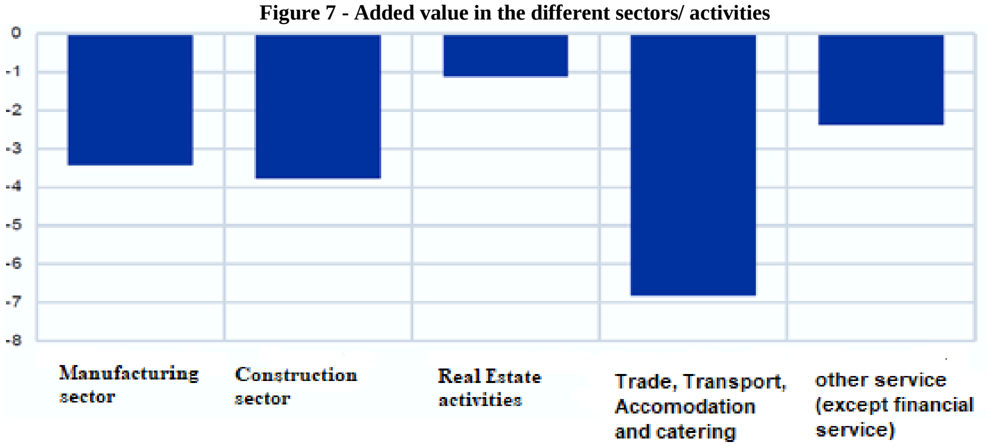
Source: based on Istat / Eurostat data.
In blue: Italian GDP, in red Euro zone GDP.

The pandemic has produced negative effects on many economic activities, but the impact of the crisis that has hit businesses has differed depending on the sector to which they belong.
In the first quarter of 2020, in the euro area, the COVID-19 pandemic caused a greater loss of added value in activities related to trade, transport, accommodation and catering compared to the manufacturing, construction and other sectors (Figure 7).

[3] Vulnerable companies are defined as companies with a negative gross operating margin (EBITDA) or with a ratio between financial charges and EBITDA exceeding 50%. Companies with non-performing loans are excluded.

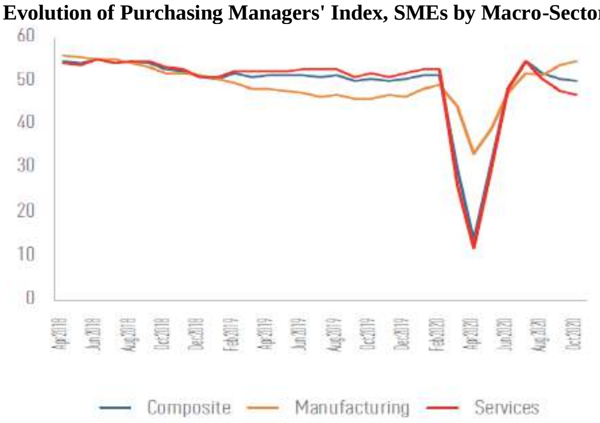
From Figure 8, it is evident that European Union companies belonging to the service sector have suffered more from the crisis than those belonging to the manufacturing sector. The PMI services index in April 2020 fell to a lower level than the manufacturing index (12 compared to 33.4) due to the pandemic. The recovery (October 2020) also highlighted a weakening of the PMI services index compared to the manufacturing sector index (48 against 53.5).

Figure 7 - Added value in the different sectors/ activities



Source: ECB (Economic Bulletin 5/2020)
From left to right: manufacturing sector, construction sector, real estate, commerce-transport-accomodation-catering, other (non-financial) services

Figure 8 - Evolution of Purchasing Managers' Index, SMEs by Macro-Sectors to which they belong



Source: Eba Risk Assessment of the European Banking System, December 2020

Unlike the previous crisis of 2007-2008, this is not a banking crisis caused by a financial shock, but rather a crisis of the real economy that exposes the banking system to new risks.
The ECB Banking Supervision has assessed the key challenges facing supervised entities over the next two to three years. The main results of the assessment are shown in the risk map of the Single Supervisory Mechanism (SSM) for 2021 (Figure 9) and in the vulnerability figure (Figure 10). These risk factors can cause an impact on banks through the most widespread internal and external vulnerabilities in the banking system itself or in the economic context in which the banks operate. Based on the current risk framework, the ECB has defined the priority areas for its supervisory activity in 2021:

a) credit risk management.
b) capital solidity.
c) sustainability of the business models.
d) governance.

a) As for credit risk management, the ECB Banking Supervision will focus on the adequacy of banks' management, operations, monitoring and internal information flows on credit risk. Particular attention will be placed on the ability of banks to identify any deterioration in asset quality at an early stage and to set up adequate and timely provisions, but also to continue to take the necessary measures to adequately manage late payments and non-performing loans. The Joint Supervisory Teams (JSTs) will review banks' practices in such areas and, if necessary, they will also conduct in-depth audits and targeted on-site and remote inspections.

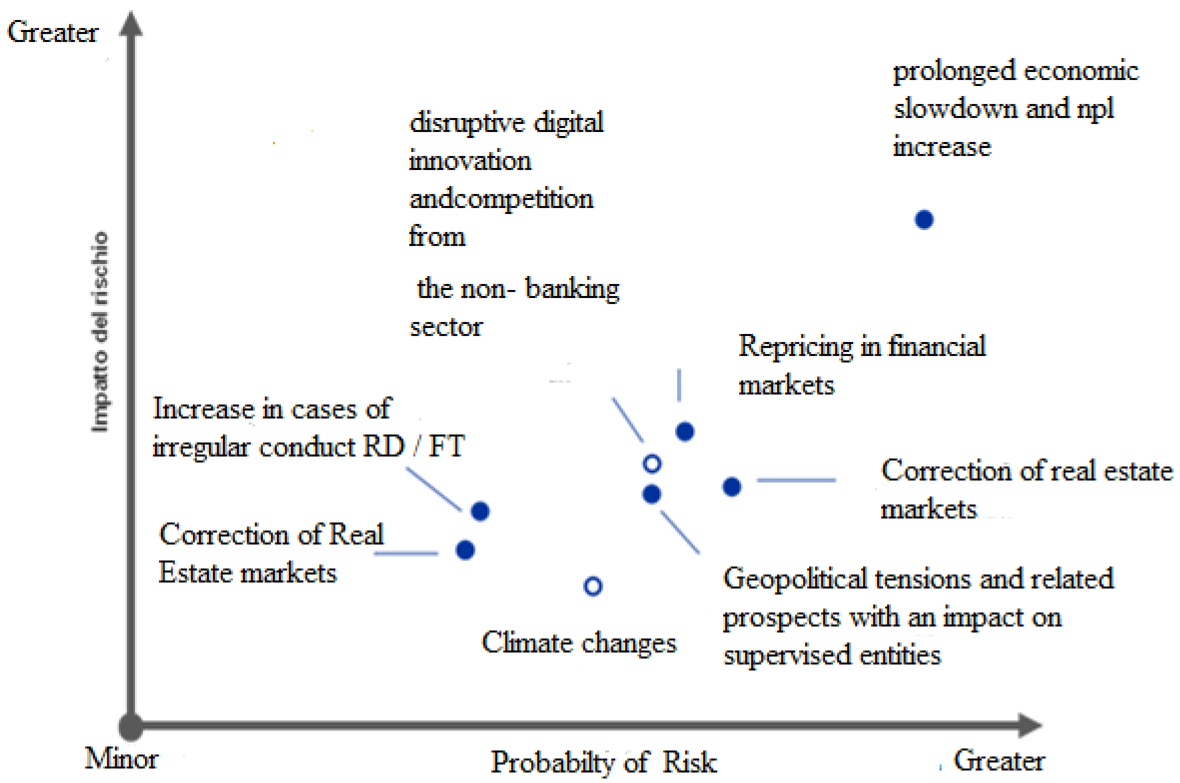
b) As regards capital strength, it is important that banks apply sound capital planning practices based on projections that can adapt to a rapidly changing environment, particularly in a crisis situation. The JSTs will then verify the adequacy of the banks' capital plans, in the light of which they will critically examine their dividend distribution and their share repurchase policies.

c) Throughout 2021, the ECB Banking Supervision will continue to review banks' strategic plans.

Additionally, since the pandemic has accelerated the digital transformation process, supervisors will assess the progress made by banks in response to such developments. Where appropriate, the JSTs will engage in a structured supervisory dialogue with bank managers regarding the oversight of corporate strategies

d) The suitability of risk management systems in crisis situations and the ability of banks to adapt and to use them appropriately in the current crisis will remain at the center of supervisory attention. The ECB Banking Supervision will discuss with banks on risk data aggregation capabilities and risk information presented to management bodies. The supervisory experts will also carry out checks on IT and cyber risk management practices and their governance, including the risks arising from the outsourcing of services to third party suppliers. Finally, the ECB Banking Supervision will continue its assessment of the prudential impact of the risks of money laundering and terrorism financing, particularly related to the banks' internal control systems.

Figure 9- Risk map of the Single Supervisory Mechanism (SSM)



Source: ECB (white circles represent risk factors that are expected to increase significantly in the next five years; the acronyms "RD / FT" and "NPL" refer respectively to money laundering and terrorist financing and to impaired loans).

On the ordinate axis, the Risk impact from lower to higher, on the abscissa axis, the Risk probability from lower to higher. From left to right clockwise: Decline in real estate markets, Increase in cases of misconduct/ money laundering / terrorist financing, Disrupting digital innovation and competition from non-banking sector, Redetermination of financial market prices, Prolonged economic slowdown and increase of NPLs, Cybercrime and IT system issues, Geopolitical tension impacting entities, Climate change.

Figure 10

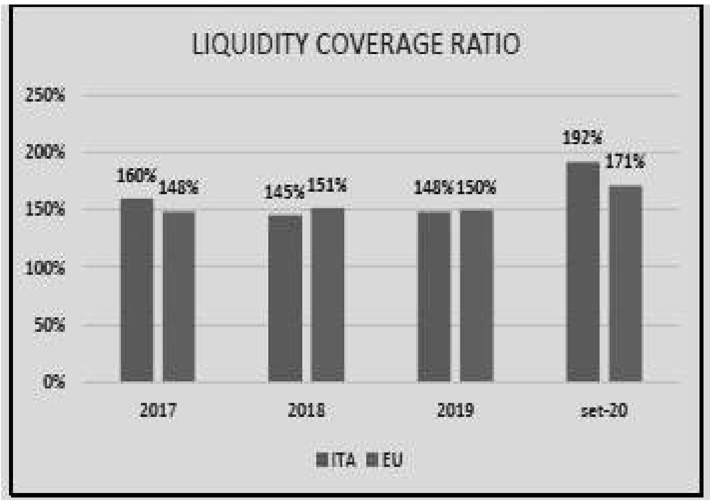
Inside the banks	weaknesses in credit risk management and hedging	structurally low levels of income and profitability	shortcomings of IT systems
	weakness of governance and strategic guidelines	persistent cost inefficiencies	
Outside the banks	high levels of public and private debt in the euro area	overcapacity in the banking sector	fragmentation of the regulatory and legal framework

Source: ECB (internal vulnerabilities can be addressed by banks themselves, while external vulnerabilities refer to the context in which banks operate).

European financial intermediaries are facing the economic crisis thanks to the availability of a good capital buffer to deal with the new credit losses that will arise. The CET1 of European banks (Source EBA[4]) was on average around 15.5% in 4Q 2020 compared to 9% recorded at the end of 2009.

In addition to broad margins of additional CET1 capital, the pandemic crisis has caught European banks (including Italian banks) with a liquidity ratio that has been growing in the past few years (Figure 11) against the minimum 100% required by the Supervisory Authorities.

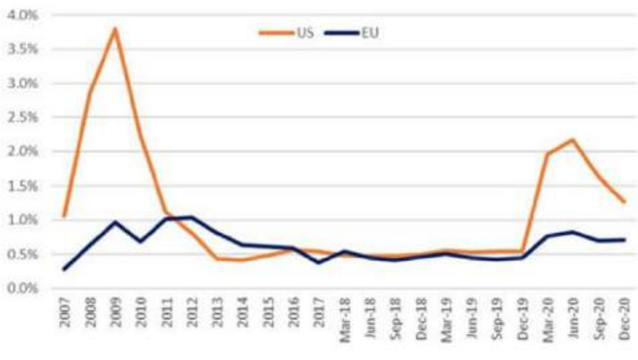
Figure 11 - LCR Italian and European Banks



Source: EBA

The COVID-19 pandemic will have a direct impact on the quality of bank assets, as further credit downgrades, an increase in distressed borrowers and a reduction in the value of collateral are likely to occur. The public support measures, including interventions by monetary, budgetary, regulatory and supervisory authorities, have produced the desired effect and thwarted a financial crisis. The great financial crisis, during which non-performing loans accumulated and saturated banks' balance sheets, taught that it is essential to identify and distinguish the purely temporary financial difficulties caused by the pandemic versus the long-lasting economic credit deterioration. Establishing adequate provisions and recognizing losses before the moratoriums and fiscal support measures expire will help avoid abrupt (cliff edge) and pro-cyclical effects that could amplify the economic cost of the pandemic. In such context, the cost of risk at the end of 2020 for European banks (higher compared to the previous year, Figure 12) stood at a value of 0.70% compared to the value of 1.27% recorded for US banks.

Figure 12 - Cost of Risk in the US and in the EU



Source: Quarterly Trends for Consolidated U.S. Banking Organizations, NY Fed; Statistical Data Warehouse (SDW), European Central Bank (ECB); and EBA supervisory reporting data

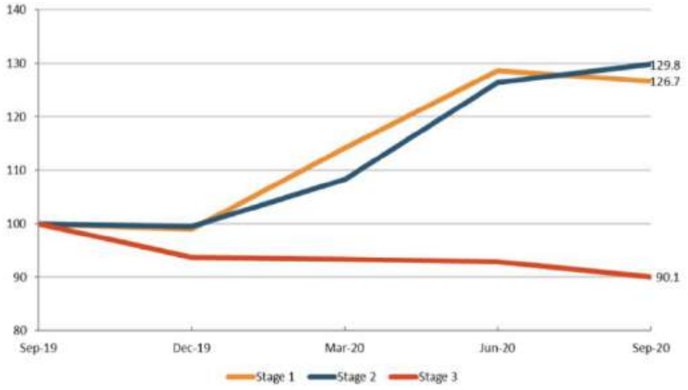
European banks (Source Dbrs Morningstar) recorded significantly lower levels of risk cost on an annual basis in the first quarter of 2021, but also in relation to all quarters of 2020 thanks to the reflection of the support provided by government measures. On a sample of 32 banks analyzed (including banks in France, Germany, Italy, the Netherlands, Spain, Sweden, Norway, Portugal, Denmark, Finland and the United Kingdom), the rating agency found an average risk cost of 31 basis points in the first quarter of 2021, far lower than that already recorded in the same period of 2020 (85 basis points) and also compared to that of the whole of 2020 (70 basis points).

In Q3 2020, European banks have increased their credit classification in stage 2 (Figure 13). In particular, in September 2020 (Source EBA[5]), EU credit institutions classified 88.6% of their credits in stage 1 (**89.5% in September 2019**), 8% in stage 2 (**6,8% in September 2019**) and 3.4% in stage 3 (3.7% in September 2019). About 20% of the loans on moratorium were classified in stage 2.

[4] See Eba, Risk Dashboard data as of Q4

[5] See EBA, ESMA, EIOPA, Risks and Vulnerabilities in the EU Financial System March 2021 (latest data available from EBA)

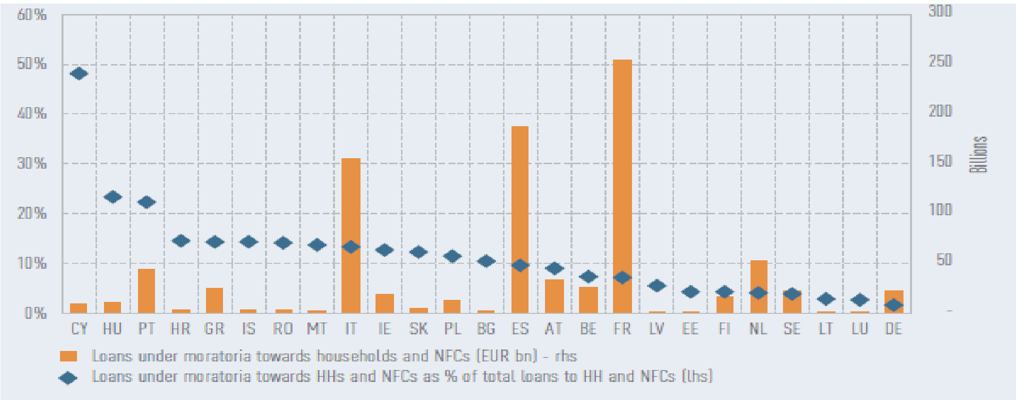
Figure 13 - Provisions for stage 1-2-3 - IFRS 9



Source: EBA supervisory reporting

With the spreading of COVID-19 in Europe and in the whole world, Member States have adopted moratoriums on loan repayments. In June 2020 (Source EBA[6]) European banks had granted a nominal volume of loans equal to € 871 billion of loan repayment moratoriums. French, Spanish and Italian banks reported the largest volumes of loans subject to a moratorium (Figure 14).

Figure 14 - Moratoriums by Country, June 2020



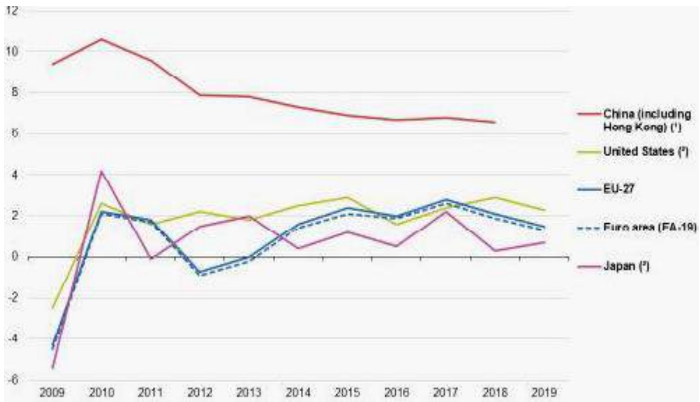
Source: Eba

In September 2020, the nominal volume of loans under moratorium was equal to 587 billion euros[7], down from the 871 billion euros recorded in June 2020 (Source EBA).

2.1. Bank Profitability

Over the last decade, the Italian banking system has faced a series of critical issues that have significantly affected the economic results of banks. The GDP of the European Union, considerably lower than that of China, Japan and the United States, has marked a significant contraction since 2009 (Figure 15) with negative impacts on banks, both on the interest margin to be gained through financing and on credit quality. The Cost of Equity (COE) for banks in the Euro Area in the period 2008-2019 was consistently higher than the ROE (Figure 16). The low profitability prospects in recent years have resulted in a decline in bank stocks on the stock market, making it more difficult for them to raise capital, when necessary.

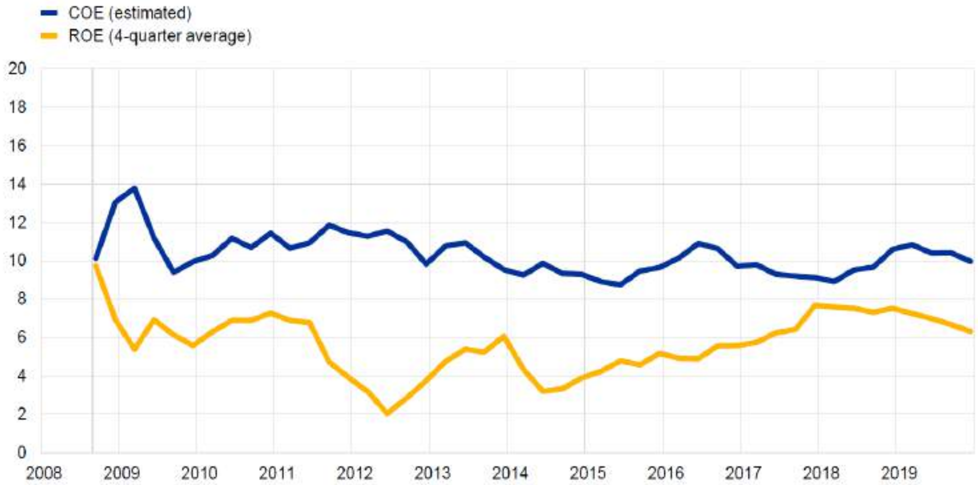
Figure 15- Real GDP 2009-2019



Source:Eurostat

[6] See EBA, Risk Assessment of the European Baking System December 2020 (latest assessment)
[7] See Risks and Vulnerabilities in the EU Financial System (March 2021 – latest available report)

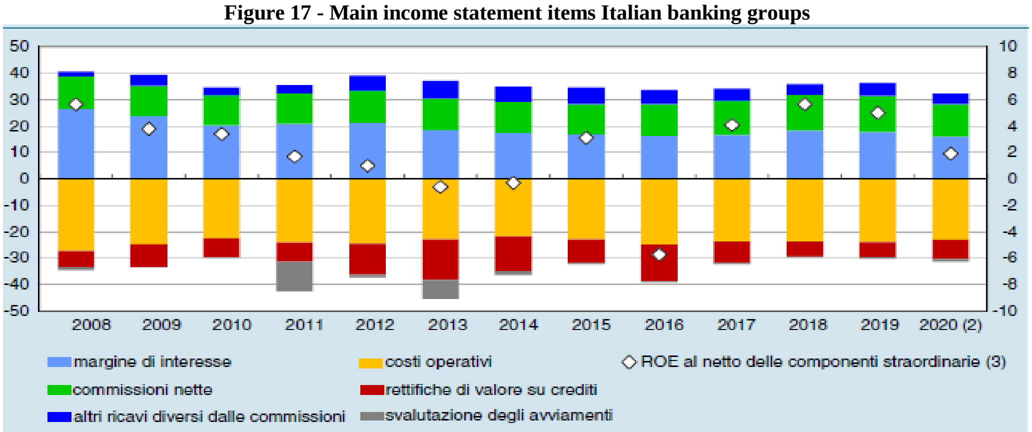
Figure 16 - ROE-COE of Euro Area Banks



Source: Bloomberg, Refinitiv, Kenneth French's data library, S&P Market Intelligence and ECB calculations.
Notes: This chart shows the time-series of the cost of equity and return on equity (ROE). Latest observation: December 2019.

Starting from February 2020, the COVID-19 pandemic has further eroded the profitability of banks despite it already experiencing a decrease in 2019. European Union credit institutions (Source Eba) recorded a ROE equal to 2.0% at the end of 2020 (Source EBA[8]), a sharp decline compared to 2019 (5.7%). Italian banks also reported a sharp decline in profitability in 2020 (Figure 17).
To better understand the evolution of banks' profitability in 2019 and 2020 in the Euro Area, Table 2 and Table 3 show the profitability and solidity indicators of the biggest Italian and European banks (Rote, CET1, NPL).
For the top three Italian banks (Table 2) there was a strong decrease in profitability in 2020 compared to the previous year, greater solidity with an increase in the CET1 ratio and better credit quality with a further decrease in NPLs (in line with the ECB perspectives).

Figure 17 - Main income statement items Italian banking groups



Source: Bank of Italy (2020)
Light blue: interest margin, green: net commissions, dark blue: other revenues (excluding commissions), yellow: operating costs, red: credit risk adjustments, grey: impairment of goodwill, white shape: ROE net of extraordinary components.

Table 2 - Top Italian Banks - Financial Statements Indicators

Top Italian Banks	Rote	CET1 Ratio	Net NPL Ratio	Rote	CET1 Ratio	Net NPL Ratio
Banca Intesa Group	6,90%	14,70%	2,60%	10,40%	13,90%	3,60%
Unicredit Group	-5,40%	15,96%	1,90%	6,70%	13,22%	1,80%
Banco BPM Group	0,19%*	14,63%	3,90%	7,56*	14,76%	5,20%

Source: author, on public budget data.
NB: * the ROTE (return on tangible equity) not published on public balance sheet data was calculated by relating net profits to tangible net assets
From left to right, for 2020 and for 2019: ROTE, CET1 Ratio, effect of net NPLs on total receivables.

For the biggest European banks in the Euro Area (Table 3) there was also a drop in profitability in 2020 compared to the previous year (Credit Agricole and Santander Bank), except for Deutsche Bank. For the Deutsche Bank Group, after a sharp decline in profitability recorded in 2019 **(Rote -11.00%),** there was a slight recovery in the profitability index in 2020 **(Rote 0.20%).**

[8] See Eba, Risk Dashboard data as of Q3 2020 and Q4 2020.

Table 3 - Top European Banks - Financial Statements Indicators

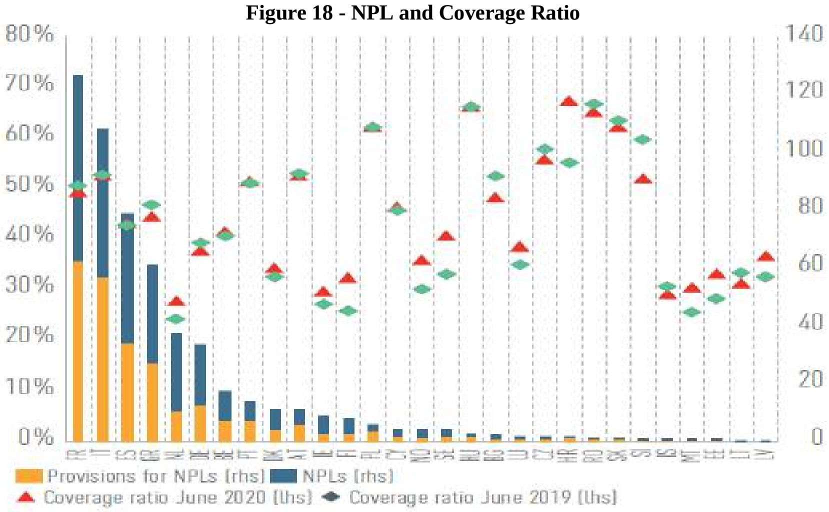
Top European Banks	Rote	CET1 Ratio	Net NPL Ratio	Rote	CET1 Ratio	Net NPL Ratio
Credit Agricole Group	9,30%	17,20%	2,40%	11,90%	15,90%	2,50%
Santander Group	1,95%	12,34%	3,21%	11,44%	11,65%	3,32%
Deutsche Bank Group	0,20%	13,60%	1,71%	-11,00%	13,60%	1,74%

Source: author, based on public budget data
From left to right, for 2020 and for 2019: ROTE, CET1 Ratio, effect of net NPLs on total receivables.

From the above data, it is clear that the main Italian and European banks in 2020 suffered from a greater decline in profitability compared to 2019. This was mainly due to:

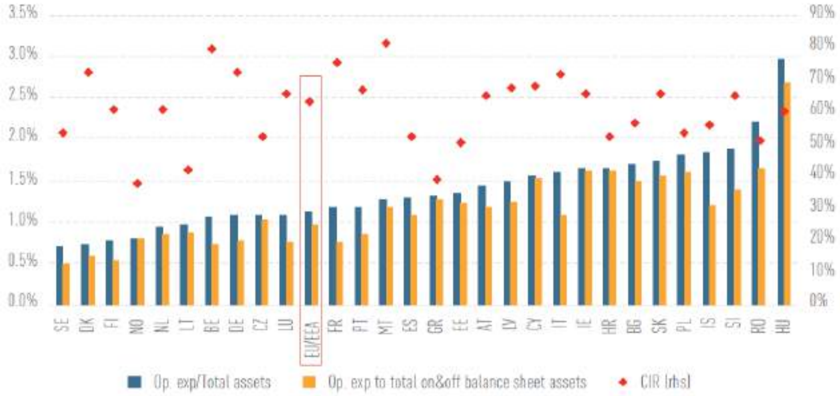
- the higher provisions on impaired loans made in 2020 (Figure 18).
- the high operating costs incurred. The cost-to-income ratio for Italian banks remained high within the Banking Union (Figure 19) with Italy recording a cost above the European average.
- a significant reduction in revenues (interest margin and commissions).

Figure 18 - NPL and Coverage Ratio



Source: EBA (Risk Assessment of the European Banking System, December 2020)

Figure 19 – Cost Income Ratio



Source: EBA (Risk Assessment of the European Banking System, December 2020)

The final challenge towards the recovery of profitability for Italian banks derives not only from the reduction of costs but also from the increased competition coming from outside the banking sector. Banks will need to consider very carefully how they can adjust their business models to accommodate this increased level of competition.

2.2. Measures adopted by international and national authorities

The resulting recession and the high level of uncertainty about the economic repercussions of the pandemic have been reflected in an increase in volatility and in risk aversion on the financial markets. All over the world, monetary authorities have adopted extraordinary expansionary measures to guarantee liquidity on the markets, to support lending to households and businesses and to stimulate the demand for goods, services and investments.
The effects observed on the financial markets and the prospects of a severe recession led the Monetary and Banking Supervisory Authorities to take very firm actions, the effect of which was supported by extraordinary fiscal policy measures.

The ECB reacted to the crisis by following two lines of action as indicated below:

- the first saw a return of Quantitative Easing (QE), with a strengthening of the existing Asset Purchase Program (APP) and with the launch of a new program of considerable size: the Pandemic Emergency Purchase Program (PEPP).
- the second relied on longer-term refinancing operations: the T-LTRO IIIs, which had been launched in 2019, and were then adapted in order for them to become even more convenient for banks.

With the former line of action, on 12 March 2020, the Governing Council of the ECB took the first step towards the reinforcement of the QE, in response to the escalating crisis. The APP, which had been restarted at the end of 2019 (monthly net purchases of 20 billion euros), was integrated with an additional 120 billion net purchase program, including both public and private securities, to be made within the end of 2020. In order to meet the expectations coming from the financial markets, on 18 March 2020 the ECB had established a new plan for the purchase of public and private securities called Pepp (Pandemic Emergency Purchase Program), initially amounting to 750 billion euros and then subsequently raised to 1,350 billion euros. The time horizon in which the ECB will conduct the purchases of securities for the pandemic emergency has been extended at least until the end of June 2021 and in any case the '**Pepp**' will continue until the ECB assesses that the coronavirus crisis is over. Following the second wave of the pandemic, the European Central Bank on10 December 2020 decided to expand the support package for the economy by increasing the Pepp debt by a further 500 billion, which thus reached a level of **1,850 billion euros** and will be extended by nine months, at least until March 2022 and in any case until the pandemic crisis is over.
The PEPP is the main response from the ECB to the downward revision of the expected inflation, linked to the pandemic; its goal is to further expand the orientation of monetary policy, adding to the other instruments already in use, and to provide support to the financing conditions for the real economy.
With the latter line of action, in March 2020 new longer-term refinancing operations (LTRO) were introduced, the conditions applied to the third series of targeted longer-term refinancing operations were made significantly cheaper (TLTRO3) and the Expanded Asset Purchase Program (APP) was bolstered.
In addition, in May 2020, the ECB launched a new series of long-term refinancing operations called pandemic emergency longer-term refinancing operations (PELTRO), to facilitate the maintenance of adequate levels of liquidity in the system even beyond the completion of the LTRO.
The European authorities moved promptly to deal with the negative impact of Covid-19 on banks, with the aim of giving them greater flexibility and protecting them from excessively procyclical phenomena.

The ECB has in fact allowed banks:

- to not comply, if needed, with some of the additional capital requirements imposed by Basel III (the so-called "capital conservation buffer" and "counter-cyclical buffer").
- to use their liquidity coverage buffer, a set of high-quality assets that under normal conditions can never fall below the expected cash outflows over the following 30 days (estimated assuming a moderately disrupted market scenario).
- to reduce by approximately 45% the amount of "common equity Tier 1" ("CET1") capital required (thanks to the possibility of using less expensive capital instruments, such as additional Tier 1 and Tier 2) to comply with the directives of the "Pillar 2 Requirement" ("P2R", a binding capital supplement that supervisory authorities annually impose on all institutions as part of the aforementioned SREP).
- to use, or to not establish, the additional capital buffer ("Pillar 2 Guidance", "P2G") that the supervisory authorities recommend to individual institutions on a non-binding basis, still within the SREP scope.
- a high degree of flexibility as regards the treatment of impaired loans (NPLs, Non-Performing Loans) both in terms of classification in UTP (Unlikely to Pay) and in terms of allocation to the income statement.
- new incentives to grant loans to SMEs as part of the revision of the conditions.

On January 27, 2021, the representatives of the 19 member States of the euro area officially approved the reform of the ESM (European Stability Mechanism), which follows that of the Eurogroup (the meeting of the Ministers of Economy of the euro member States) of November 2020, positively welcomed by the Euro Summit (the meeting of the Heads of State and government of the countries belonging to the euro area) of December 2020. The revision of the Treaty establishing the ESM was necessary to strengthen the functioning of the Economic and Monetary Union and favor the completion of the Banking Union. The reform will further develop the ESM toolkit and strengthen the role of the Single Mechanism in the design, negotiation and monitoring of financial assistance programs. Such changes will reinforce the resilience and problem-solving capabilities in the euro area.
The fragilities created for the effective and orderly management of banking crises made it appropriate to activate the common backstop of the Single Resolution Fund operating through the ESM.
The backstop, introduced with the ESM reform, represents a safety net in support of banks in crisis through the last resort guarantee in support of the Single Resolution Fund (SRF) which is activated only in the presence of unmanageable systemic banking crises and differs significantly from the financial support tools with which the ESM has been equipped so far.

The Backstop safety net will therefore have the following features:

- enhancement of confidence in the European banking sector through the possibility of resorting to an instrument of last resort in the event of worsened conditions.
- activation, in order to finance the resolution of one or more failing banks, in the event that the Single Resolution Fund is temporarily insufficient.
- preventing the resolution of failing banks from happening at the expense of taxpayers, by strengthening the resolution mechanism and at the same time recovering costs from the banking sector.

The Italian government also promptly approved measures to support businesses and individuals in need of liquidity. The measures introduced include those relating to the granting of state guarantees on loans (through SACE guarantees and guarantee funds for SMEs) and the partial or total moratorium measures on loans (see Legislative Decree 18 / 2020 - "Cura Italia" Decree).
Through the Budget Law 2021 (L. 178/2020), the moratorium on loans for micro, small and medium-sized enterprises was extended to 30 June 2021 with the aim of better supporting businesses. With the "Sostegni Bis" Decree, the moratorium on loans to SMEs has then been extended until 31 December 2021 but only upon request from eligible companies and only in relation to the principal repayment. The 2021 Budget Law (L. 178/2020) has also introduced a new incentive to business combination processes (including for banks) carried out through mergers, demergers or company transfers. In particular, it was established that, in the event of a merger, demerger or transfer of a company, approved by the shareholders' meeting, or by the different body competent by law, between 1 January 2021 and 31 December 2021, the transformation of the deferred tax asset (DTA) into a tax credit is permitted, in favor of the subject resulting from the merger or incorporating entity, of the beneficiary and of the transferee. The maximum amount of convertible DTAs cannot exceed 2% of the combined total assets of the parties participating in the merger or demerger.

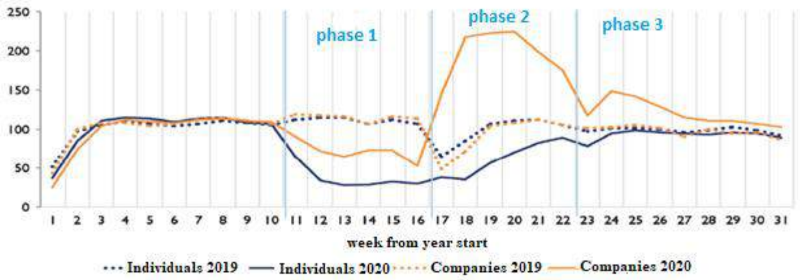
The EBA published the Guidelines for the classification of moratoriums immediately after the outbreak of the pandemic (April 2020), providing indications aimed at guiding the approach of financial institutions regarding the management of non-performing and forborne exposures.
More specifically, if the moratorium is deemed 'EBA Compliant', the automatic attribution of the status of Forborne is not mandatory.
At the end of September 2020, the EBA granted banks an extension of the credit moratoriums until 30 June 2021. Following the extensions of the national moratoriums that took place on 30 December 2020, the EBA also issued some FAQs (Frequently Asked Questions) at the end of January which provided some specific clarifications, in particular:

- moratoriums are deemed as "EBA compliant" when their duration does not exceed 9 months.
- in the event of a moratorium granted or extended before 30 September 2020 for a duration of more than 9 months, they are in any case deemed as "EBA compliant".
- any concessions or extensions after 30 September 2020 must remain within the duration of 9 months to be EBA compliant, otherwise, the delta NPV (Net present value) has to be verified on the extension date - only after 1/1/21 - and so has the forbearance.
- any extension made on existing moratoriums is deemed as an amendment to the contract made from the moment it was activated.

2.3. Italian banking sector during the pandemic crisis

The liquidity crisis that hit Italian companies following the pandemic has found an efficient response from Italian banks. During this crisis, credit institutions have taken on a completely different role compared to the last recession of 2008, when they were part of the problem. With their new social function, today banks have in fact a leading role in providing the solution. The health condition of the banking sector has changed compared to the previous financial crisis, thanks to a more robust capital situation already recorded starting from 2019, which explains the substantial steadiness of the ecosystem and an enhanced expertise in managing non-performing loans, that have undergone a sharp decline since 2016. Loans dispensed by intermediaries have increased significantly and diffusely across sectors and among companies of different sizes, including the smallest.
The economic support measures adopted by the Government and by the European Institutions have put Italian banks in the position to grant credit to businesses at very low rates, thus playing a complementary role with respect to public sector interventions and monetary policy (Figure 20 - phase 2).

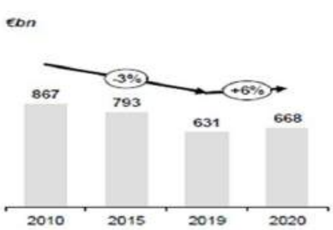
Figure 20- Number of renewals and new allocations from Italian banks in 2020 to companies and individuals



Source: Eurisc. on the ordinate axis, the index number with the 2019 average being = 100; on the abscissa axis, the week from year start, and the indication of Phase 1, Phase 2 and Phase 3. Blue dots: Individuals – 2019, Blue line: Individuals – 2020, Red dots: Companies – 2019, Red line: Companies - 2020

In 2020, the increased stock of loans to businesses (Figure 21) reflects the measures to support credit access introduced by the Government (moratoriums and guarantees on new loans), as well as the flexibility inherent in the rules of classification of loans, according to the guidelines indicated by Supervisory Authorities.

Figure 21- Stock Business loans



Source: Strategy &, based on Bank of Italy data

Italian banks are also supporting businesses and households in 2021: in April 2021, disbursements exceeded the value observed the previous year by 4.2% (Table 4).

Table 4 - Bank Lending in Italy

	Totale impieghi settore privato e PA *		settore privato *		di cui: a famiglie e società non finanziarie	
	mld €	var. % a/a (1)	mld €	var. % a/a (1)	mld €	var. % a/a (1)
apr-16	1.810,5	0,3	1.540,3	0,4	1.402,5	0,3
apr-17	1.797,5	0,5	1.530,4	0,7	1.400,0	1,1
apr-18	1.771,8	2,4	1.506,9	2,9	1.367,7	2,5
apr-19	1.702,5	0,9	1.436,2	1,0	1.296,5	1,0
apr-20	1.687,9	1,0	1.422,1	1,2	1.282,4	1,5
mag-20	1.689,0	1,0	1.425,1	1,3	1.286,1	1,7
giu-20	1.696,9	1,5	1.436,3	2,0	1.294,0	2,8
lug-20	1.706,0	1,9	1.445,4	2,6	1.304,1	3,3
ago-20	1.703,5	2,5	1.443,7	3,4	1.305,1	4,2
set-20	1.711,5	2,5	1.453,4	3,6	1.313,8	4,7
ott-20	1.712,5	2,9	1.454,9	4,0	1.316,6	5,0
nov-20	1.721,1	3,4	1.462,1	4,4	1.324,0	5,4
dic-20	1.709,8	3,9	1.453,0	4,4	1.308,6	5,5
gen-21	1.709,9	3,8	1.449,0	4,3	1.309,5	4,9
feb-21	1.710,7	4,2	1.447,0	4,6	1.310,3	5,2
mar-21	1.718,8	3,1	1.456,7	4,0	1.316,9	4,6
apr-21	1.715,6	3,1	1.454,0	3,8	1.314,0	4,2

Source: ABI (Monthly Report May 2021)

From left to right: total loans (private sector and public administration), private sector (sub-total: households and non-financial businesses).

In recent years, the Italian banking system has fortified its credit quality with a substantial improvement in all the main asset quality performance indicators. This is due to three main factors:

i) the improvement of the macroeconomic context, also following the financial and economic crises recorded between 2008 and 2012.
ii) important NPL deleveraging operations through the sale of non-performing loan portfolios to third parties.
iii) the strengthening of structures and management processes for granting, monitoring and credit recovery.

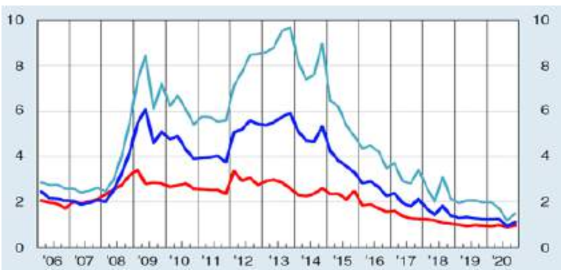
In December 2020 the stock of gross impaired loans (Source Bank of Italy) reached 103.6 billion euros (down by approximately 33%) compared to the first half of the year which had marked a stock of 133.7 billion euros, while the net stock was equal to 50.5 billion euros.

Net non-performing loans recorded in March 2021 (Source: ABI Research Department based on Bank of Italy data[9]) amounted to approximately 19.9 billion euros, down compared to the 20.9 billion euros recorded in December 2020. The net bad loans ratio on total loans decreased to 1.15% in March 2021 (it was 1.53% in March 2020, 1.84% in March 2019 and 4.89% in November 2015).

The flow of new impaired loans (Figure 22) in relation to performing loans, which remained almost stable until September 2020 (equal to 0.9%), grew in the fourth quarter of 2020 reaching 1.1%. The increase affected both loans to households (from 0.9% to 1.0%) and those to businesses (from 1.2% to 1.5%). The indicator increased mainly in sectors which had been badly exposed to the effects of the crisis such as services.

In the second half of 2020, the persistence of economic uncertainty also led to a further increase in the amount of performing loans for which the banks observed a significant increase in credit risk. The incidence of loans classified in stage 2 on the total of performing loans increased, gross of value adjustments, from 10.2% to 10.7%. In December 2020, the coverage rate of all performing loans reached 0.6% (up by 9 basis points in a year).

Figure 22 - Deterioration rate



households businesses total economy

Source: Bank of Italy (Financial Stability Report 1/2021). Red line: households, light blue: companies, bright blue: economic system.

Table 5 presents the exposures of impaired loans recorded in December 2020 which show that the greatest exposures of bad loans are concentrated in companies operating in the services sector.

9 See ABI Monthly Report, May 2021

Table 5 - Exposure of impaired loans by type of customer (1)

(Billion euro and percentage values; December 2020)

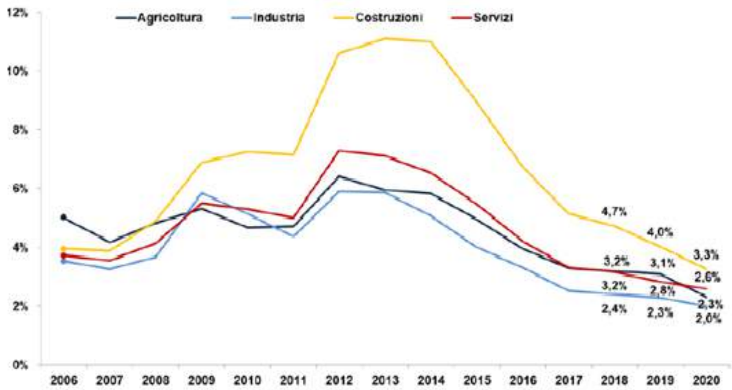
ITEMS	Gross exposures	share of total gross receivables (2)	Net exposures	share of total net receivables (2)	Real guarantees (3)	Personal guarantees (3)	coverage rate for unsecured loans
				Businesses (4)			
Impaired loans to customers	67	9,6	29	4,4	32	13	64,3
of which : manufacture	14	6,8	5	2,7	4	3	68,6
construction	17	24,8	7	12,4	10	3	64,3
services	33	8,7	15	4,2	16	7	61,8
of which: bad loans	33	4,6	10	1,6	15	8	76,2
of which : manufacture	6	3,2	2	1,0	2	2	77,3
construction (5)	8	12,2	3	4,8	4	2	75,6
services	16	4,2	5	1,5	7	4	75,7
				Consumer households			
Impaired loans to customers	20	3,8	10	2,1	13	1	65,7
of which: bad loans	9	1,8	4	0,7	6	0	78,3
				Total sectors (6)			
Impaired loans to customers	93	6,0	42	2,9	47	14	63,2
of which: bad loans	43	2,8	15	1,0	21	9	76,4

Source: Bank of Italy (Financial Stability Report 1/2021)

(1) The data are taken from unconsolidated financial statements, which do not include loans granted by financial companies belonging to banking groups and by foreign subsidiaries. "Non-current assets and groups of assets held for sale" are included, which at the end of December 2020 amounted to approximately 6 billion euro for total impaired loans before adjustments. Provisional data. - (2) The shares are calculated, gross and net of the related value adjustments, in relation to the corresponding gross and net exposure to the single sector and subsector of reference. - (3) The amount corresponds to the gross exposure amount covered by a guarantee (real or personal). - (4) The business sector, in addition to manufacturing, construction and services, also includes agriculture, forestry, fishing and other industrial activities other than manufacturing. - (5) also includes real estate activities. - (6) also includes the sectors "Public Administration", "Financial and insurance companies", "Non-profit institutions serving households" and "Non classifiable and non-classified units".

From analyzes carried out by Cerved (Figure 23), in 2020 the deterioration rates recorded for businesses have had a different intensity by counterparty macro-sector. The sectors that recorded the highest reductions in defaulted new loans are those of **agriculture** (from 3.1% in 2019 to 2.3% in 2020) and **construction** (from 4.0% to 3.3%). **Industry** remains the sector with the lowest deterioration rates, reaching 2% (from 2.3% in 2019), while **services** have fallen by 0.2% (from 2.8% in 2019 to 2.6% in 2020).

Figure 23 - Non-financial companies deterioration rate by macro-sector



Source: ABI-Cerved

Deterioration rates by macro sector - number of credit positions that deteriorate during the year in relation to the stock of non-impaired positions at the beginning of the same year. Dark blue line: Agriculture, light blue line: Industry, yellow line: Construction, Red line: Services.

The extraordinary measures in support of businesses adopted during the pandemic have so far prevented the blocking of economic activities and the subsequent restrictions due to the health emergency from translating into a surge in corporate defaults.

The Italian banking system, together with the Spanish and French banking systems, was one of the main users of the moratorium tool (Figure 24): over 300 billion euro granted to 2.7 million entities (Source ABI). This allowed a freezing of NPLs and a strong acceleration of the dynamics of loans to non-financial companies (+ 8.5% yoy in December net of the moratoriums granted, the maximum since the end of 2008, +63 billion euro) above the average of the euro area.

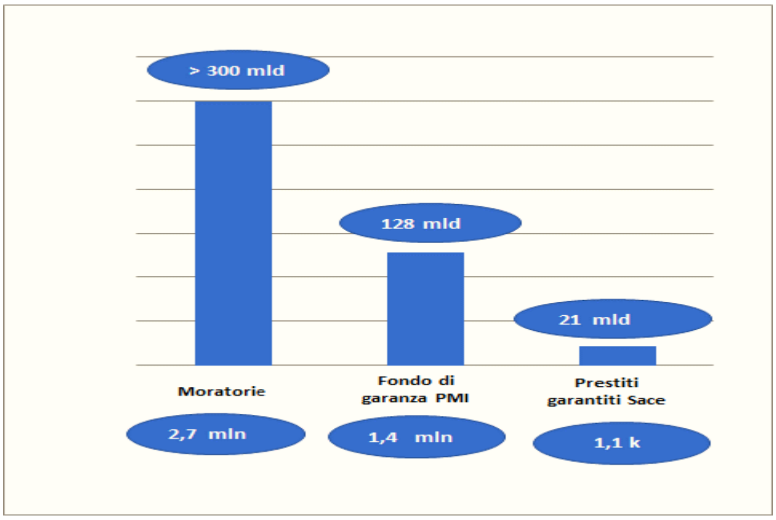
At the end of December 2020 (Source: Bank of Italy[10]), the CET1 ratio of the entire system was on average equal to 15.5% of risk-weighted assets (an increase compared to the 13.9% recorded at the end of 2019).

The improvement affected both significant and less significant banks (respectively 70 and 130 basis points, at 15.5% and 18.7%) and largely reflects the decrease in RWAs, which fell by 3.7% and 1.4%.

The decline was affected not only by the re-composition of assets in the portfolio towards less risky exposures by some of the main groups, but also by the effects of public guarantees granted to facilitate access to credit by households and businesses, which contributed to reducing the average weighting of risk assets.

[10] See Bank of Italy, Financial Stability Report 1/2021

Figure 24 - Moratoriums and guarantees given

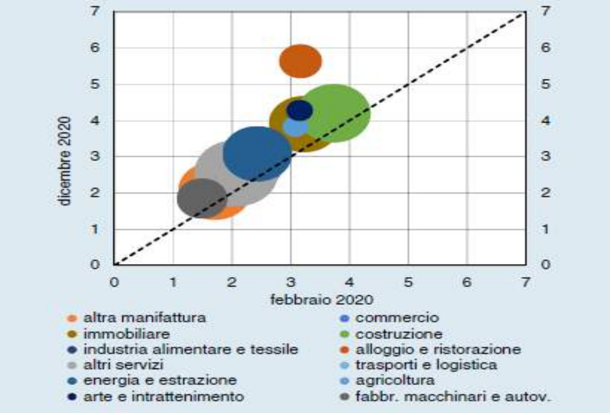


Source: Author, based on ABI data.
From left to right: moratoriums, SME guarantee fund, SACE guaranteed loans

3. Prospective situation of the economic and financial system in Italy after Covid

The Covid-19 pandemic has hit the Italian economy more than other European countries. In 2020, the gross domestic product fell by 8.9%, compared with a decline in the European Union of 6.4% (Source Istat / Eurostat).
In the first quarter of 2021, Italy's GDP recorded an increase of 0.1% (Source Istat) compared to the previous quarter, against a decline in the European Union which showed a quarterly decline of 0.1% (Source Eurostat). The Bank of Italy estimates a growth of Italian GDP of over 4.0% for 2021.
The crisis has hit an already fragile situation from an economic, social and environmental point of view. Between 1999 and 2019, the GDP in Italy grew by 7.9% (Source MEF). In the same period in Germany, France and Spain, the increase was respectively 30.2%, 32.4% and 43.6%.
The recession triggered by the Covid-19 epidemic in 2020 has increased the number of businesses with liquidity needs and capital deficits. The main support measures launched by the government between March and August 2020 have greatly mitigated these effects.
However, the use of new loans, also thanks to public guarantees, further expands debt, especially for riskier companies.
The granting of public guarantees to small and medium-sized enterprises has proved to be an effective tool to support banks that grant the loans required to cope with the crisis. However, the medium-term effects of public guarantees depend both on the duration of the guarantees and on the other policy measures that will be adopted.
At the end of 2020, many economic forecasts referred to the situation emerging from the COVID-19 pandemic. Estimates on the conditions of households and businesses when exiting the Covid crisis predict a worsening of their ability to meet debt service commitments.
According to the Bank of Italy and Cerved data (Figure 25 and Table 6), the deterioration of the creditworthiness of companies, when support measures will cease, will be significant, especially in some sectors (accommodation and catering, art and entertainment, real estate).

Figure 25 - Deterioration of creditworthiness



Source: Bank of Italy (Financial Stability Report 2/2020). Orange: manufacturing sector (other), brown: real estate, dark blue: food industry and textile, light grey: other services, medium blue: energy and extraction, black: art and entertainment, light blue: commerce, green: construction, red: accommodation and catering, pastel green: transport and logistics, pastel blue: agriculture, dark grey: machinery and vehicles.

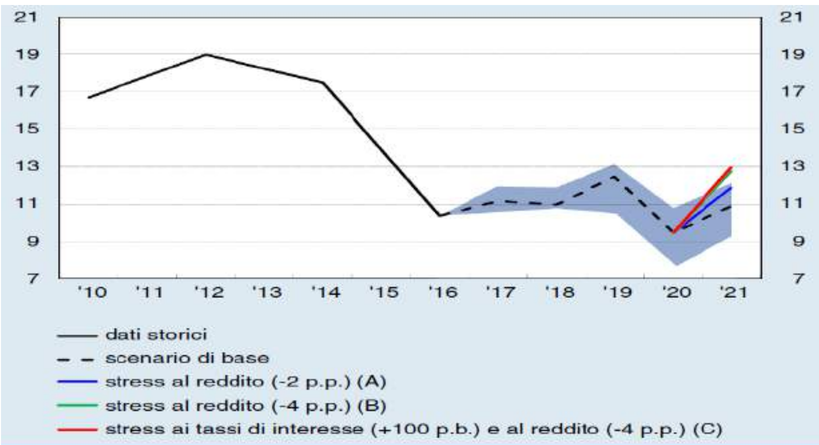
Table 6- Evolution of the probability of default (PD) by sector

Totale	**4,5%**	**5,1%**	**6,0%**
Manufacturing (except the specified subcategories)	3,6%	4,4%	5,7%
Manufacturing – Equipment	3,2%	4,0%	4,9%
Electricity, gas, steam and air conditioning supply	5,0%	3,7%	4,0%
Water supply; sewerage; waste management and remediation activities	4,3%	4,2%	4,5%
Constructions	7,1%	7,3%	8,7%
Wholesale and retail trade (except the specified subcategories)	3,8%	4,7%	5,6%
Transporting and storage	4,8%	5,7%	8,4%
Accommodation and food service activities	6,4%	8,7%	11,9%
Information and communication	5,0%	5,2%	4,4%
Real Estate	6,0%	5,8%	6,4%
Professional, scientific and technical activities	3,6%	3,9%	4,4%
Administrative and support service activities	5,0%	5,7%	6,5%
Tourism related supporting activities	5,8%	11,0%	14,3%
Agriculture	5,7%	6,4%	6,9%
Textile and clothing	4,2%	5,3%	6,9%
Di cui: componente manifatturiera	*4,1%*	*5,2%*	*6,9%*
Di cui: componente commercio e dettaglio	*4,5%*	*4,7%*	*5,6%*
Pharmaceutics	3,1%	2,8%	2,5%
Di cui: componente manifatturiera	*2,5%*	*2,5%*	*2,3%*
Di cui: componente commercio e dettaglio	*3,4%*	*3,0%*	*2,5%*
Automotive	3,8%	5,2%	6,0%
Di cui: componente manifatturiera	*3,7%*	*5,0%*	*6,7%*
Di cui: componente commercio e dettaglio	*3,8%*	*5,3%*	*5,7%*
Food and beverage	4,1%	4,7%	4,6%
Di cui: componente manifatturiera	*3,8%*	*4,5%*	*4,1%*
Di cui: componente commercio e dettaglio	*4,6%*	*4,9%*	*5,3%*
Fuel	3,0%	3,6%	4,7%
Di cui: componente manifatturiera	*2,4%*	*2,9%*	*6,1%*
Di cui: componente commercio e dettaglio	*3,1%*	*3,6%*	*4,5%*
Other sectors	5,0%	6,2%	7,1%

Source: Cerved Rating Agency. For sectors Textile and clothing, Pharmaceutics, Automotive, Food and beverage, Fuel, a breakdown is provided of the manufacturing component and of the trade and retail component.

The share of debt held by vulnerable firms (those with negative EBITDA or financial charges/EBITDA ratio above 50%) could increase significantly in case of adverse scenarios (Figure 26) in 2021, even if it would not reach the levels observed after the 2008 crisis and that of 2011. There is the possibility that vulnerable companies could turn into zombie[11] companies in the post-Covid period, contaminating the solvency of a few banks. The presence of zombie companies can be a cause but also a consequence of the presence of weak banks and as such reluctant to recognize the size and impact of non-performing loans on their balance sheets (bank forbearance, evergreening, zombie lending). Zombie companies damage the economic system by trapping productive factors that could be allocated for more profitable uses.

Figure 26 - Share of debt held by companies



Source: Bank of Italy based on Cerved data (Financial Stability Report 2/2020).
Black line: historical data, dashed line: base scenario, blue line: stress on income (-2 PP) (A), green line: stress on income (- 4PP) (B), red line: stress on interest rates (+100 bps) and on income (-4 PP) (C).

Many factors lead to fear an increase in NPLs within banks in the two-year period 2021-2022: contraction of GDP, evolution of the risk appetite of operators (of uncertain direction, but characterized by high variability); public debt situation; general institutional

[11] *Zombie* is a company that operates at a loss and with very little hopes of recovering the economic equilibrium (non-viable), which would typically be forced to major reorganization or directly expelled from the market, but which nevertheless avoids bankruptcy thanks to the support it receives from lenders.

strength (legal system, efficiency of litigation processes, degree of adherence to the rule of law, predictability of rules) and specific institutional strength (quality of corporate governance); level of profitability and capitalization of the banking sector and capacity for provisions.

The factors that influence the NPL dynamics can be attributed to:

- **external factors**: GDP (main), unemployment rate, risk aversion level, inflation, interest rates, exchange rate, public debt (crowding out, bank assets quality, fiscal space), share prices (guarantees), legal system quality
- **internal factors**: bad management, bad luck, skimping (low investments in selection and monitoring), provisions, capitalization, loan growth, competition level, size, leverage, revenue diversification, profitability.

The European Union responded to the pandemic crisis with Next Generation EU (NGEU), a EU funding plan for the recovery of Europe from the economic consequences of the pandemic, which provides for a budget of 750 billion euros (of which 191.5 billion euros for Italy) put in place to oppose the effects of the coronavirus and allow the countries that will use it to restart their economy by investing in a series of sectors that constitute a priority for Europe such as green transition, innovation, education and health. The plan defined as National Relaunch and Resilience Plan (PNRR) approved at the end of April 2021 by the Italian Council of Ministers will encourage the relaunch of growth and productivity of the Italian economy.
The banking system will play an essential role in involving relevant companies in the strategic sectors of construction, technology, information, transport, manufacturing, electronics, energy. Many of these involved companies are SMEs that will need new capital to face robust investments to finance strategic dimensional growth with the needed process- and sometimes product-innovations. The credit consortia (in Italy, Confidi) will be a very effective ally for businesses to deal with the NGEU, through business consultancy which will prove to be crucial in investment choices.
On a macro scale, public spending financed by EU Next Generation funds may affect the growth expectations of businesses, and therefore their employment and investment decisions. In such context, it will be essential to direct resources towards uses that increase the productivity of the Italian system rather than towards unproductive forms which would leave the country with all the issues unsolved, once their direct impact has been exhausted. Only by embarking on a long-term growth path can the short-term effects of the pandemic be mitigated and the sustainability of public debt in the long term still be guaranteed.
The Covid-19 crisis will accelerate pre-crisis trends as subdued growth and low interest rates will persist for a long time. And this will test the resilience of the financial system and the regulatory reforms implemented after the global financial crisis.
While banks may benefit from temporary regulatory flexibility, digitalization will increase the appeal of financial services. The banking sector can move from traditional oligopoly to a system with a few dominant platforms that control access to a fragmented customer base, with a few BigTech companies and a few traditional operators transformed into platforms that control the interface with customers. Midsize banks will suffer as they are unable to handle the cost efficiencies and IT investments that are crucial in the new environment. Consolidation could be an escape route for troubled banks, but in the post-Covid-19 world, political obstacles to cross-border mergers could re-emerge as States become more protective of their domestic banking champions, with banks being considered as strategic. The current crisis will accelerate structural changes, including bank consolidation and acquisitions and mergers can be a very important factor. Consolidation of the banking sector can be an important factor in helping to address overcapacity and fragmentation potentially leading to synergies and greater efficiency. A few banks are currently proving to be too small with respect to competitiveness requirements. It is assumed that large banks have greater efficiency and resilience capabilities than small and medium-sized ones. Regulators must adapt to the digital revolution by balancing the incentive towards competition and the benefits of innovation with the protection of financial stability. To this end, they need to coordinate prudential regulation and competition policy with data-related policies, navigating amid complex trade-offs. The regulatory reforms launched following the global financial crisis and the supervisory action carried out in the past decade, in particular since the years of the sovereign debt crisis, have had significant effects both on the capitalization of banks and on the consistency of impaired loans. As a result, the ability of Italian banks to deal with adverse shocks has significantly increased. However, the scale of the current crisis could be such as to require significant action. We expect to see resilience and unstable performances among Italian banks in the coming years, as the recession will affect asset quality and overall financial profiles. In the multiplicity of new regulations and supervisory expectations, which banks have complied with in recent years or on which they are currently engaged, there are a few regulatory systems (such as the new definition of default) which effects will unfold in an economic context that makes their pro-cyclical features rather alarming. In particular, the pro-cyclical nature of such measures lies in the direct link between the difficulties of the economy and the growth of NPLs, economic difficulties which in turn are exacerbated by regulatory policies that trigger a restriction of the credit supply. This pro-cyclical nature is extremely worrying in a situation like the current one, characterized by a profound economic crisis that requires, on the contrary, counter-cyclical measures aimed at fueling the supply of credit (very appropriately implemented through the highly indulgent monetary policy of the ECB). Although banks can benefit from a certain degree of regulatory flexibility, it is necessary, however, that they use this flexibility carefully, without postponing the surfacing of highly probable losses. Faced with this situation, Banks have activated several interventions to prepare for the cliff effect deriving from the end of the accomodating measures. The available evidence suggests that the increase in credit adjustments recorded in the first half of this year is absorbed by larger intermediaries (Source: Bank of Italy), in the face of difficulties that appear to be widespread. All banks must equip themselves with suitable tools to spot the increase in the vulnerability of debtors in good time, especially those who have adhered to moratoriums, for which available information might be limited at this stage. In the coming years, it will therefore be essential to continue to manage NPLs effectively to prevent them from accumulating in balance sheets, hindering the strengthening actions and undermining market and investor confidence. The progress made so far is significant: from the collection of granular and standardized data on bad loans to the creation of organizational units specifically dedicated to recovery, from the preparation of reduction programs to the launch of a market for transactions on this type of asset. Despite the crisis, during year 2020 Italian banks seem to have overcome the severe recession without significant damages, managing to sell an amount of non-performing loans only slightly lower than what was planned before the outbreak of the pandemic.

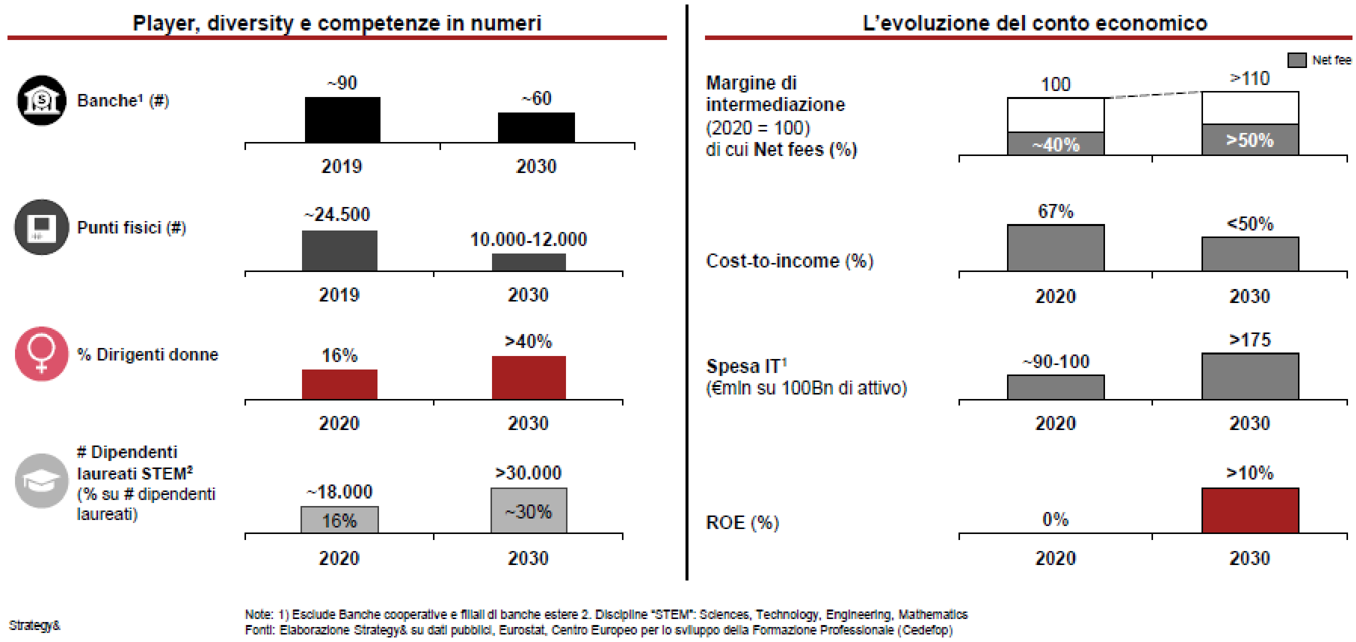
The challenge of continuing in this direction must now be faced, ensuring full support to the economy and simultaneously maintaining suitable capital levels.

In the future (Vallino Convention Aifirm 15 December 2020) the system is moving towards the direction of fewer branches (a process strongly accelerated by the pandemic), multi-bank and outsourced low value cash services, important role of robotics and artificial intelligence, tech bank company, dichotomy between low-cost banking services (self-service, digital and "package" formulas) and high added value services (asset management, non-standardized loans), revision of human resources management system and inception of new types of contracts that provide remote services and flexibility.
The COVID-19 pandemic will probably accelerate a few dynamics that already have begun in the banking sector (Enria, 2020):

- Digital transformation favored by widespread adoption of remote working, growth in demand for digital products and services, unbundling of traditional services.
- Need to address structurally low levels of profitability; considerable efforts to reduce costs have already been achieved: cost-to-income ratio dropped from 56.6% in 2014 to 54.4% in 2019.

In light of the new dynamics, banks (Figure 27) are therefore called upon to redesign the models, orienting them towards:
1. "remote / face-to-face" hybrid operating models.
2. "branch / digital" hybrid distribution models.
3. hybrid "in / out" sourcing models enabled by cloud, architectures and platforms.

Figure 27



On the left-hand side: players, diversity and skills, in numbers. From top to bottom: Banks (#), Branches (#), % Female executives, STEM Graduate employees (# and % on graduate employees).
On the right-hand side: the evolution of the income statement. From top to bottom: Brokerage Margin (2020 = 100), of which Net Fees (%), Cost-to-income (%), IT spending (€mln on 100 bln assets), ROE (%).

Source: Strategy &
(1)excludes cooperative banks and branches of foreign banks; 2) STEM disciplines: Sciences, Technology, Engineering, Mathematics. Source: Strategy& elaboration on publicly available data, Eurostat, European Center for the Development of Professional Training (Cedefop).

The implementation of digital banking platforms will allow the automatic delivery of traditional and innovative banking products, which will reach the customer directly through websites. According to estimates by Allied Market Research, the global market for digital banking platforms in 2019 was worth 3.95 billion dollars. In 2027 it will have reached a value of 10.87 billion dollars, growing at an annual CAGR rate of 13.6%. Alongside the quantitative growth, there will be a qualitative evolution of services, made possible by the adoption of artificial intelligence and machine learning technologies.

Conclusions

The Covid-19 pandemic, which has devastated the world since the early months of 2020, suggests that there is still a long way to go. The outbreak of the pandemic hit Italy when it was already in a phase of slowing growth, which for years has remained lower than that of the most advanced economies. At European level, the response from the institutions was rapid: suffice it to think of the activation of the general safeguard clause of the Stability and Growth Pact, which for the first time allowed all member States to temporarily deviate from the medium-term budgetary goals. The ECB and other supervisory and regulatory authorities have adjusted their supervisory strategy to changing circumstances. The Central Bank intervened in a timely manner in order to stabilize the markets and create the necessary conditions to ensure the correct transmission of monetary policy impulses to the real economy. The monetary policy measures adopted by the Supervisory Authority have provided an essential contribution to support the recovery of the Eurozone economy. The nature of the current crisis makes international cooperation more essential than ever to ensure effective and timely measures to support economic activity.

Any coordination failures could jeopardize the quick economic recovery.
In the face of uncertain macroeconomic prospects, any increase in insolvencies, the more likely to happen, the longer the economic stagnation lasts, will lead to an increase in bad debts for banks and, likely, to a credit rationing which in turn would enhance the recession. The main objective is to avoid the credit crunch that occurred during the past financial crisis and also to develop the secondary market for NPLs.
The EU Commission encourages the creation of national asset management companies (AMCO) controlled by the States which could buy non-performing loans on the market from banks in crisis and it also encourages their cooperation through the establishment of a European network to create synergies. Banks, supported in getting rid of NPLs from AMCO, will be able to continue to finance healthy businesses and households.
Credit has acquired and acquires a crucial role, in the most acute phases of the crisis, to ensure the necessary liquidity for households and businesses hit by significant shocks both from the demand side and from the supply side of productive factors. The support to credit in the subsequent phase will be equally important, to sustain companies along their path towards restoring sound economic conditions to their businesses, in a context of uncertainty that is likely to linger for a long time.
The European banking regulatory framework, conceived in a completely different context from the current one, reveals a few critical issues that must absolutely be addressed in order to avoid a damaging restriction of the credit supply and social impacts on households and businesses.
However, a positive note comes from the fact that in recent years European banks have recovered their capital strength and improved the quality of their assets. In such context, both the measures aimed at mitigating the risk of debtor default and the strategies that will be put in place to support the economic recovery remain essential.
The role of European institutions in the current period of crisis has been crucial, but it is now necessary to implement regulatory simplifications and rapid and effective strategies which will allow companies to survive in the post-Covid 19 crisis. It is also necessary to implement all those European regulatory simplification initiatives aimed at helping banks to expand their lending to businesses.

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Deep Learning for seasonality modelling in Inflation-Indexed Swap pricing

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Abstract

An Inflation-Indexed Swap (IIS) is a derivative in which, at every payment date, the counterparties swap an inflation rate with a fixed rate. For the calculation of the Inflation Leg cash flows it is necessary to build a mathematical model suitable for the Consumer Price Index (CPI) projection. For this purpose, quants typically start by using market quotes for the Zero-Coupon swaps in order to derive the future trend of the inflation index, together with a seasonality model for capturing the typical periodical effects. In this study, we propose a forecasting model for inflation seasonality based on a Long Short Term Memory (LSTM) network: a deep learning methodology particularly useful for forecasting purposes. The CPI predictions are conducted using a FinTech paradigm, but in respect of the traditional quantitative finance theory developed in this research field. The paper is structured according to the following sections: the first two parts illustrate the pricing methodologies for the most popular IIS: the Zero Coupon Inflation-Indexed Swap (ZCIIS) and the Year-on-Year Inflation-Indexed Swap (YYIIS); section 3 deals with the traditional standard method for the forecast of CPI values (trend + seasonality), while section 4 describes the LSTM architecture, and section 5 focuses on CPI projections, also called inflation bootstrap. Then section 6 describes a robust check, implementing a traditional SARIMA model in order to improve the interpretation of the LSTM outputs; finally, section 7 concludes with a real market case, where the two methodologies are used for computing the fair-value for a YYIIS and the model risk is quantified.

Key Words:
Inflation-Indexed Swap (IIS), Year-on-Year Inflation Indexed Swap (YYIIS), Zero-Coupon Inflation-Indexed Swap (ZCIIS), Seasonality model, CPI bootstrap, Machine Learning (ML), Deep Learning, Long Short-Term Memory (LSTM) Network

1) Introduction

Inflation has been rising since the end of 2020, mainly due to the reopening of the economy after the pandemic crisis. Despite central banks suggesting that this type of inflation will be transitory, market participants seem to believe otherwise. Financial institutions and investors base their expectations on two main clues: on one hand, the several constraints that the international supply chain have to currently face, and on the other hand, the financial stimuli that governments from all over the world have adopted to encourage their national economies.

While nobody knows with certainty how high inflation will rise or how long it will persist, the expectations, that this round of inflation will not be so short as promised, have given investors an incentive for reconsidering financial products, able to protect the holder from the detrimental effects of the inflation; products that only in the recent past were almost disappeared.

The present paper is part of this strand of literature and it aims to shed light on the seasonality modeling in Inflation Indexed Swaps (IIS), a derivative contract in which, at every payment date, the counterparties swap an inflation rate with a fixed interest rate.

This study aims to extend the existing literature concerning the integration of machine learning in the field of quantitative finance. Machine learning methodologies are in fact increasingly spreading in the financial sector. Among the numerous examples of applications proposed by literature, the most popular ones are mainly aimed at solving the following problems:

- Input data quality (Pendyala, 2018)
- Innovative algo-trading techniques (De Prado, 2018)
- Optimal portfolio management (Heaton *et al.*, 2017)
- Pattern recognition and classification (Kim, 2017)
- Financial time-series forecasting as an alternative to traditional econometric approaches (ARIMA, Bayesian VAR, GARCH) (Mammadi, 2017; Yanui, 2017)

It is more difficult to find evidence in the literature of artificial intelligence methodologies applied to exotic financial instruments pricing or about the integration of traditional quantitative finance theory with the new FinTech methodologies. The traditional implementation regards the numerical solution of the so-called fundamental Black-Scholes-Merton PDE through Radial Basis Functions (Company *et al.*, 2018). Only more recently, the application of Regressive Neural Networks together with Monte Carlo method was suggested for evaluating early-exercise features in American and Bermuda option pricing in accordance with Longstaff-Schwartz methodology (Lelong and Lapeyre, 2020).

While the number of studies adopting machine learning techniques in the field of finance has grown quite rapidly, the field of research focusing on the identification of the seasonality effects with such methodologies is still limited. The research aims to bridge this gap proposing an innovative approach, through the design of a so-called long short-term memory (LSTM) network for the identification of the seasonality effects. In particular, the study implements a deep learning methodology able to consider potential highly nonlinear relationships between the values of the Consumer Price Index (CPI), sampled in the previous five years in accordance with the most common market standard convention. In fact. Bloomberg® and other well-known info-providers set this parameter equal to five years in their valuation platforms (e.g., the Bloomberg® SWIL and SWPM pricing modules). This setting is also adopted in the design of the LSTM network with the aim of maintaining this trading practice and of helping the interpretation of the results using the same market conventions. It is worth to note that the frequency of the sample in the considered time series is monthly: this is also a standard choice for the analysis of this index, given that it reflects the publishing time interval.

2) The pricing framework

An Inflation-Indexed Swap (IIS) is a swap deal in which, for each payment date, $T_1, \dots, T_M$, counterparty A pays to counterparty B the inflation rate in the considered period, while counterparty B pays to counterparty A the fixed rate. The inflation rate is calculated as the percentage return of the CPI over the reference time interval.

There are two main types of IIS traded on the market: the Zero-Coupon Inflation-Indexed Swap (ZCIIS) and the Year-on-Year Inflation-Indexed Swap (YYIIS) (Brigo and Mercurio, 2006).

In a ZCIIS, at the maturity date T_M, assuming $T_M = M$ years, counterparty B pays to counterparty A the fixed quantity:

$$\boldsymbol{N[(1+K)^M - 1]} \quad (1)$$

Where K and N are the fixed interest rate and the principal, respectively.
In return for this fixed payment, at the maturity date T_M, counterparty A pays to counterparty B the floating amount:

$$\boldsymbol{N\left[\frac{I(T_M)}{I_0} - 1\right]} \quad (2)$$

Where $\boldsymbol{I_0}$ is the reference CPI and $\boldsymbol{I(T_M)}$ is the value of the index at time $\boldsymbol{T_M}$.
In a YYIIS, for each payment date T_i, counterparty B pays to counterparty A the fixed amount:

$$\boldsymbol{N\varphi_i K} \quad (3)$$

Where φ_i is the year fraction of the fixed swap leg in the range $[T_{i-1}, T_i]$, $T_0 \coloneqq 0$ and N is the principal of the deal.
Counterparty A pays to counterparty B the floating amount equal to:

$$\boldsymbol{N\varphi_i\left[\frac{I(T_i)}{I(T_{i-1})} - 1\right]} \quad (4)$$

ZCIIS and YYIIS are typically quoted in terms of the corresponding equivalent fixed rate K.

2.1) Zero-Coupon Inflation-Indexed Swap (ZCIIS) pricing

The standard arbitrage-free pricing theory leads to the estimation of the fair value for a ZCIIS inflation leg at time t, $0 \le t \le T_M$ (Brigo and Mercurio, 2006):

$$\boldsymbol{ZCIIS(t, T_M, I_0, N) = N \cdot E_n\left\{exp\left(-\int_t^{T_M} n(u)du\right)\left[\frac{I(T_M)}{I_0} - 1\right]\middle|\, \mathrm{F}_t\right\}} \quad (5)$$

Where F_t is the σ-algebra generated by the stochastic process of the underlying up to time t.
The nominal price of a zero coupon bond is equal to the price of a contract that pays one unit of the CPI Index at bond maturity. In formulas, for each $t < T$:

$$\boldsymbol{I(t)P_r(t,T) = I(t)E_r\left\{\exp\left(-\int_t^T r(u)du\right)\middle|\, \mathrm{F}_t\right\} = E_n\left\{\exp\left(-\int_t^T n(u)du\right)I(T)\middle|\, \mathrm{F}_t\right\}} \quad (6)$$

Then Equation (5) becomes:

$$\boldsymbol{ZCIIS(t, T_M, I_0, N) = N\left[\frac{I(t)}{I_0}P_r(t, T_M) - P_n(t, T_M)\right]} \quad (7)$$

Where $\boldsymbol{P_n(t, T_M)}$ is the Zero-coupon bond price at time $\boldsymbol{t}$ for the maturity $\boldsymbol{T}$ in the nominal economy and $\boldsymbol{P_r(t, T_M)}$ is the Zero-coupon bond price at time $\boldsymbol{t}$ for the maturity $\boldsymbol{T}$ in the real economy.

Equation (7) for a valuation at time $t = 0$ simplifies to:

$$\boldsymbol{ZCIIS(0, T_M, N) = N[P_r(0, T_M) - P_n(0, T_M)]} \quad (8)$$

Equations (7) and (8) lead to an important result in the evaluation of the derivative because the pricing formula is independent from the model assumptions given that it follows from the absence of arbitrage. As a result, we are able to unambiguously derive the prices for the zero-coupon bonds starting from the quoted prices of the zero-coupon inflation-indexed swaps (Mercurio, 2005).
In fact, by equating (8) with the actualized nominal value of (1) and obtaining $P_n(0, T_M)$ from the current curve of the nominal zero-coupons, we are able to solve the equation for the unknown quantity $P_r(0, T_M)$.
Therefore, we get:

$$\boldsymbol{P_r(0, T_M) = P_n(0, T_M)[1 + K(T_M)]^M} \quad (9)$$

(Kazziha, 1999) defined the T-forward CPI at time t as the fixed quantity X to be exchanged at time T for the CPI $I(T)$, for which such a swap has a zero value.
From formula (6), we get

$$\boldsymbol{I(t)P_r(t,T) = XP_n(t,T)} \quad (10)$$

The value at time 0 of a T_M-forward CPI can be obtained from the market quotation of $K(T_M)$ applying the formula:

$$\boldsymbol{I_M(0) = I(0)\cdot[1+K(T_M)]^M} \quad (11)$$

This result is perfectly equivalent to (9).

2.2) Year-on-Year Inflation Indexed Swap (YYIIS) pricing

Pricing a YYIIS is more complicated than the ZCIIS: the pay-off value at time T_i , $t < T_i$ is

$$\boldsymbol{YYIIS(t,T_{i-1},T_i,\psi_i,N) = N\psi_i E_n\left\{\exp\left(-\int_t^{T_i} n(u)du\right)\left[\frac{I(T_i)}{I(T_{i-1})}-1\right]\middle|\, \mathrm{F}_t\right\}} \quad (12)$$

Assuming $t < T_{i-1}$, we can estimate:

$$\boldsymbol{N\psi_i E_n\{\exp\left(-\int_t^{T_{i-1}} n(u)du\right)E_n\{\exp\left(-\int_{T_{i-1}}^{T_i} n(u)du\right)\left[\frac{I(T_i)}{I(T_{i-1})}-1\right]\middle|\, F_{t-1}\}|F_t\}} \quad (13)$$

The inner expectation in Equation (13) is the $ZCIIS(T_{i-1},T_i,I(T_{i-1}),1)$:

$$\boldsymbol{N\psi_i E_n\left\{\exp\left(-\int_t^{T_{i-1}} n\,du\right)[P_r(T_{i-1},T_i)-P_n(T_{i-1},T_i)]|\,\mathrm{F}_t\right\}} =$$
$$= \boldsymbol{N\psi_i E_n\left\{\exp\left(-\int_t^{T_{i-1}} n(u)du\right)[P_r(T_{i-1},T_i)]\middle|\,\mathrm{F}_t\right\} - N\psi_i P_n(t,T_i)} \quad (14)$$

The last expected value can be seen as the nominal price of a derivative that pays the price of the zero coupon bond, $P_r(T_{i-1},T_i)$ in nominal unit at time T_{i-1}. If the real rates were deterministic, then this price would be the discounted value, in nominal terms, of the forward price of the real bond. In this case we would have:

$$\boldsymbol{E_n\left\{\exp\left(-\int_t^{T_{i-1}} n(u)du\right)[P_r(T_{i-1},T_i)]\middle|\,\mathrm{F}_t\right\} = P_r(T_{i-1},T_i)P_n(t,T_{i-1}) = \frac{P_r(t,T_i)}{P_r(t,T_{i-1})}P_n(t,T_{i-1})} \quad (15)$$

However, the real rates are stochastic and the expectation is model-dependent. Here, we propose the YYIIS pricing according to the Jarrow-Yildirim (JY) model (Jarrow and Yildirim, 2003).
Denoting by Q_n^T the T-forward nominal measure for a generic maturity T and E_n^T the associated expectation, we can write:

$$\boldsymbol{YYIIS(t,T_{i-1},T_i,\psi_i,N) = N\psi_i P_n(t,T_{i-1})E_n^{T_{i-1}}\{P_r(T_{i-1},T_i)|\mathrm{F}_t\} - N\psi_i P_n(t,T_i)} \quad (16)$$

Recalling the zero-coupon bond price formula in accordance with the Hull-White model (Brigo and Mercurio, 2006):

$$\boldsymbol{P_r(t,T) = A_r(t,T)\exp[-B_r(t,T)\cdot r(t)]} \quad (17)$$

where:

$$\boldsymbol{B_r(t,T) = \frac{1}{a_r}[1-\exp[-a_r(T-t)]]} \quad (18)$$

$$\boldsymbol{A_r(t,T) = \frac{P_r^M(0,T)}{P_r^M(0,t)}\exp\{B_r(t,T)f_r^M(0,t) - \frac{\sigma_r^2}{4a_r}[1-\exp(-2a_r t)]B_r(t,T)^2\}} \quad (19)$$

And considering that the instantaneous real rates evolve under $Q_n^{T_i-1}$, according to the stochastic differential equation:

$$\boldsymbol{dr(t) = [-\rho_{n,r}\sigma_n\sigma_r B_n(t,T_{i-1}) + \vartheta_r(t) - \rho_{r,I}\sigma_I\sigma_r - a_r r(t)]dt + \sigma_r dW_r^{T_{i-1}}(t)} \quad (20)$$

with $W_r^{T_{i-1}}$ a Brownian motion under the $Q_n^{T_i-1}$ measure, we get:

$$\boldsymbol{YYIIS(t,T_{i-1},T_i,\psi_i,N) = N\psi_i P_n(t,T_{i-1})\frac{P_r(t,T_i)}{P_r(t,T_{i-1})}\exp[C(t,T_{i-1},T_i)] - N\psi_i P_n(t,T_i)} \quad (21)$$

where:

$$C(t,T_{i-1},T_i) = \sigma_r B_r(T_{i-1},T_i)[B_r(t,T_{i-1})(\rho_{r,I}\sigma_I - \frac{1}{2}\sigma_r B_r(t,T_{i-1}) + \frac{\rho_{n,r}\sigma_n}{a_n+a_r}(1+a_r B_n(t,T_{i-1}))) - \frac{\rho_{n,r}\sigma_n}{a_n+a_r}B_n(t,T_{i-1})] \quad (22)$$

In the Yarrow-Yildirim model (Jarrow and Yildirim, 2003), the expected value for the price of a zero-coupon bond under a nominal forward measure is equal to the current forward price of the bond multiplied by a correction factor, which depends on the instantaneous volatility of the nominal rate, σ_n, of the real rate σ_r, of the CPI σ_I and on the instantaneous correlation between the real rate and the CPI $\rho_{r,I}$.
The exponential of C represents the mentioned correction term: this takes into account the stochasticity of the real rates and, consequently, is zero for $\sigma_r = 0$. The value at time t of the swap inflation-indexed leg is obtained through the summation of all floating payments. Therefore:

$$YYIIS(t,\mathcal{T},\Psi,N) = N\psi_{\iota(t)}[\frac{I(t)}{I(T_{\iota(t)-1})}P_r(t,T_{\iota(t)}) - P_n(t,T_{\iota(t)})] + N\sum_{i=\iota(t)+1}^{M}\psi_i[P_n(t,T_{i-1})$$

$$\frac{P_r(t,T_i)}{P_r(t,T_{i-1})}\exp[C(t,T_{i-1},T_i)] - P_n(t,T_i)] \quad (23)$$

Where: $\mathcal{T} \coloneqq \{T_1,\dots,T_M\}$, $\Psi \coloneqq \{\psi_1,\dots,\psi_M\}$ and $\iota(t) = \min\{i: T_i > t\}$ where the first payment after time t has been priced according to (7).

Setting $t = 0$ we get the pricing formula evaluating the leg as of today (Mercurio, 2005):

$$YYIIS(0,\mathcal{T},\Psi,N) = N\psi_1[P_r(0,T_1) - P_n(0,T_1)] + N\sum_{i=2}^{M}\psi_i\left[P_n(0,T_{i-1})\frac{P_r(0,T_i)}{P_r(0,T_{i-1})}\exp[C(0,T_{i-1},T_i)] - P_n(0,T_i)\right] \quad (24)$$

3) CPI index traditional simulation

Through (11), we are able to project the index values in the future according to the swap rates listed on the market following the pricing framework. Since the frequency with which the index is published is monthly, it is necessary to provide a simulation of the CPI with such periodicity (Caligaris and Giribone, 2018). The missing curve points are therefore estimated by adding the logarithm of the monthly increase between a calculated value $\mathfrak{I}_M(0)$ and its subsequent value $\mathfrak{I}_{M+1}(0)$:

$$\Delta\mathfrak{I}_M = \frac{\ln\left(\frac{\mathfrak{I}_{M+1}(0)}{\mathfrak{I}_M(0)}\right)}{12\cdot\tau} \quad (25)$$

Where τ is the time interval expressed in year fraction between $\mathfrak{I}_M(0)$ and $\mathfrak{I}_{M+1}(0)$.
The points making up the simulated curve of the consumer price index are defined by the formula:

$$\mathfrak{I}_{i+1} = \mathfrak{I}_i\exp(\Delta\mathfrak{I}_M + \mathfrak{R}_M), \mathfrak{I}_M(0) \le \mathfrak{I}_i \le \mathfrak{I}_{M+1}(0) \quad (26)$$

The standard methodology, suggested by the main benchmark info provider pricing modules, takes into account the index seasonality algebraically adding the normalized residuals $\mathfrak{R}_M$ obtained from the historical values of the CPI, in accordance with the expression (27):

$$\mathfrak{R}_M = \frac{\sum_{i=1}^{stagyear}\ln\left[\frac{\mathfrak{I}_{i+1}^{Monthly}}{\mathfrak{I}_i^{Monthly}}\right]}{stagyear} - \frac{\sum_{i=1}^{12\cdot stagyear}\ln\left[\frac{\mathfrak{I}_{i+1}^{Monthly}}{\mathfrak{I}_i^{Monthly}}\right]}{12\cdot stagyear} \quad (27)$$

Where $\mathfrak{R}_M$ are the standardized residuals obtained from the effect of seasonality over $stagyear$ years. The first contribution is the logarithmic variation of the CPI values on the considered month; the second one represents the overall logarithmic variation recorded in the time period considered for seasonality.

The objective of this study is to propose a deep learning methodology (LSTM network) able to simulate the seasonality of the inflation index. In this way, in addition to introducing a more robust and flexible econometric methodology than the standard one, the integration between the classical quantitative finance theory together with Fintech paradigms can be considered an interesting feature (Bonini *et al.*, 2019).

In fact, the determination of the swap fair value is implemented by applying the formulas described above for the ZCIIS and YYIIS and therefore in total agreement with canonical principles; moreover, a Long Short-Term Memory network will be implemented for a more reliable simulation of the CPI seasonality. The next paragraph deals with the explanation of the architecture for a standard LSTM network.

4) LSTM network architecture and training procedure

LSTM networks are also able to learn long-term relationships between the time intervals of a time series, therefore without the need to pre-set the number of time lags, as occurs in other dynamic recurrent networks, such as Nonlinear AutoRegressive (NAR) and Nonlinear Auto-Regressive with exogenous variables (NARX) (de Simon-Martin *et al.*, 2020).

A common LSTM unit is composed of a cell, an input gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. Intuitively, the cell is responsible for keeping track of the dependencies between the elements in the input sequence. The input gate controls the extent to which a new value flows into the cell, the forget gate controls the extent to which a value remains in the cell and the output gate controls the extent to which the value in the cell is used to compute the output activation of the LSTM unit (Hochreiter and Schmidhuber, 1997). The activation function of the LSTM gates is often the logistic sigmoid. Figure 1 shows how the flux of a data sequence Y with C features (or channels) of length S has been processed into a LSTM layer. In the block diagram, h_t and c_t are, respectively, the output (also known as hidden state) and the cell state at time t.

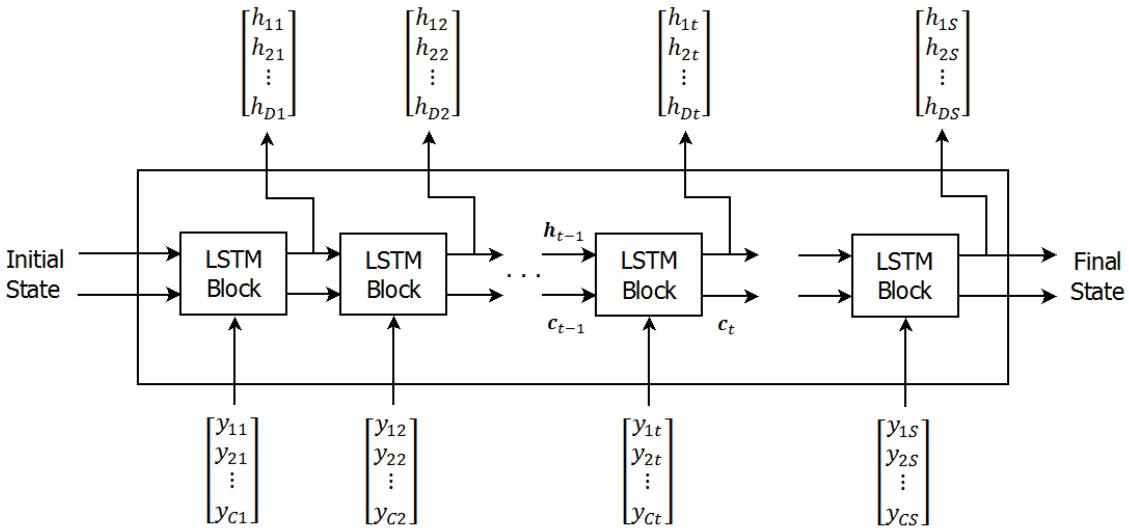

Figure 1. LSTM network architecture

The first LSTM block uses the initial state of the network and the first time-step of the sequence in order to compute the first output and the first update of the cell state. At time t, the block uses the current state of the network (c_{t-1}, h_{t-1}) and the next step of the sequence for estimating the output and updating the current state of the cell c_t. The layer state is characterized by the hidden state (also known as the output state) and the cell state. The hidden state at time step t contains the output of the LSTM layer for the current time step. The cell state contains the information learnt in the previous steps. For each time step, the layer adds or removes information from the cell state. The layer controls these updates using gates. The following components control the cell state and the hidden state of the layer (Hochreiter and Schmidhuber, 1997):

- Input gate (i): Control level of cell state update
- Forget gate (f): Control level of cell state reset (forget)
- Cell candidate (g): Add information to cell state
- Output gate (o): Control level of cell state added to hidden state

Fig. 2 shows how the gates (i, f, g, o) process the signal at time t

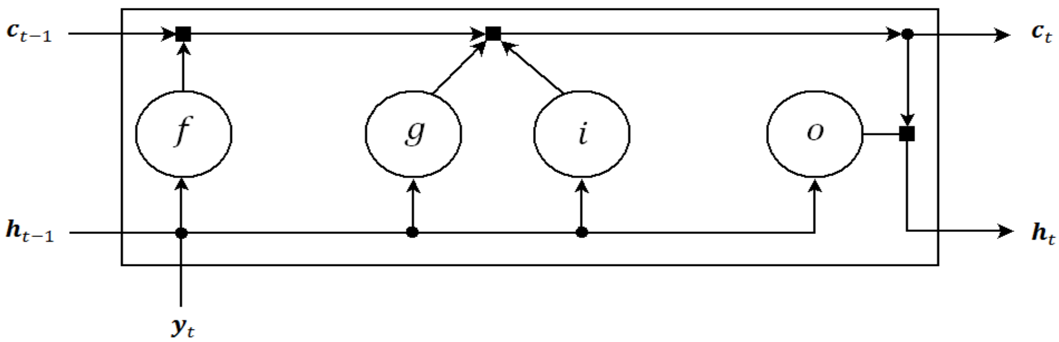

Figure 2. Signal processed by the gates

In a LSTM, the parameters that are subjected to calibration are: the input weights (W), the recurrent weights (R) and the biases (b) (de Simon-Martin *et al.*, 2020). W, R and b are the arrays built through the concatenations of such parameters for each component: $W = (W_i, W_f, W_g, W_o)^\top R = (R_i, R_f, R_g, R_o)^\top b = (b_i, b_f, b_g, b_o)^\top$
where i, f, g and o denote the input gate, the forget gate, the cell candidate and the output gate, respectively.
At time step t, the cell state is given by:

$$\boldsymbol{c_t} = \boldsymbol{f_t} \odot \boldsymbol{c_{t-1}} + \boldsymbol{i_t} \odot \boldsymbol{g_t} \quad (28)$$

Where $\odot$ is the Hadamard product operator.
At time step t, the hidden state is given by:

$$\boldsymbol{h_t} = \boldsymbol{o_t} \odot \boldsymbol{\sigma_c(c_t)} \quad (29)$$

Where σ_c is the activation function of the state (typically a hyperbolic tangent).

The following equations define the components at time step t:

- Input gate (i): $\boldsymbol{i_t = \sigma_g(W_i y_t + R_i h_{t-1} + b_i)}$ (30)
- Forget gate (f): $\boldsymbol{f_t = \sigma_g(W_f y_t + R_f h_{t-1} + b_f)}$ (31)
- Cell candidate (g): $\boldsymbol{g_t = \sigma_c(W_g y_t + R_g h_{t-1} + b_g)}$ (32)
- Output gate (o): $\boldsymbol{o_t = \sigma_g(W_o y_t + R_o h_{t-1} + b_o)}$ (33)

σ_g is the activation function of the gate, which is typically a sigmoid.

LSTMs are supervised networks, as a result, after the design of the model, it is essential to implement a robust algorithm for the training phase. This is the part in which the designer decides how many neurons must be implemented in order to make reliable predictions. In order to obtain valid models for forecasting purposes it is necessary to conduct statistical and econometric tests. The objective of the first kind of test is to tune the LSTM in order to have a good fitting of the training dataset.
The gap between the target and the model output is reduced through an ADAM optimizer as the network training process progresses, so it may happen that the estimated relationship returns a perfect fit of the sampled data (in-sample), making vain the attempt at generalization, fundamental for making the network capable of processing different data (out-of-sample).
For this reason and especially in the field of deep learning where there is a huge number of parameters to tune in order to capture highly non-linear relationships, special measures for avoiding overfitting must be taken into consideration. As a result, the first intervention, shared also with traditional recurrent networks, such as NAR and NARX, is to work directly on the dataset through a random-splitting method. The data set configuration used for the network is:

- 70% of the set will form the training set, thus the optimization will be carried out with respect to its loss function (J) only.
- 15% of the set will be assigned to the validation set, thus, despite the weights being updated with respect to the train set, the algorithm saves the weights that minimize J on the validation set, in order to avoid data overfitting and trying to reach a good generalization.
- 15% of the data set will form the test set, so that the network performance can be measured on data that it has never seen before, as the ultimate objective of a neural network user is to employ the network on completely new data.

The second kind of statistical measures, which are traditionally applied in the field of deep learning, work directly on the network. The implemented measures can be summarized as follows:

- Adding a term to the traditional loss function ($RMSE$) which put in a penalty (the λ coefficient) if a further weight (ω) associated to an arch has been activated:

  $$\boldsymbol{J = RMSE + \frac{1}{2}\lambda\|\omega\|^2} \quad (34)$$

- Dropout, which is a technique consisting of training only a group of randomly selected neurons rather than the entire network: a percentage (a popular choice is 25%) determines how many neurons to choose and the remaining ones are deactivated. Since the neurons and the relative weights are continuously modified, it is thus possible to avoid overfitting.

These metrics are thus implemented in the forecaster in order to have a reliable fitting.
Given that the objective is to perform a prediction of the most reasonable CPI projections, we also implement a test which has an econometric nature. It is based on the verification of the autocorrelation error absence so that the model error is unstructured and the predicted values can be econometrically reliable.

5) Comparison between standard and LSTM techniques for the CPI projection

In order to compare the standard inflation bootstrap methodology with the LSTM approach, we use the market data retrieved from Bloomberg on 31st December 2020. Swap rate values, $K(T_M)$, quoted by the market at the reference date are reported in Table 1, together with the estimation of the CPI projections, $\mathfrak{I}_M(0)$ and the $\Delta\mathfrak{I}_M$, according to Formula (11) and (25). The estimation of $\Delta\mathfrak{I}_M$ is useful in order to have the inflation values expressed on monthly basis (Giribone, 2020). According to Equation (26), this information allows us to project the CPI values for the next 10 years using a market-oriented approach without taking into account the seasonality. In order to add this essential contribution for the forecast into the model, we have to consider the monthly normalized residuals, $\mathfrak{R}_M$, calculated starting from the past CPI realizations. The traditional way to implement this task is to apply Equation (27). Using the traditional market standard preference to consider the previous five years of the CPI time-series, we get the $\mathfrak{R}_M$ reported in the second column of Table 2. Applying recursively equation (26), the projections for the CPI are obtained for the following years. These simulations are reported in Fig. 3 together with the past values. The black line represents the past five years CPI values used for the estimation of the seasonality effect; the blue line represents the CPI projections without seasonality: it connects the blue dots which are the $\mathfrak{I}_M(0)$ whose estimations are strictly connected to the $K(T_M)$ quotation and the red line represents the projections of the CPI index taking into account the seasonality through the monthly annualized residuals $\mathfrak{R}_M$. According to this approach, we have a "ready-to-use" seasonality model that is able to take into consideration market-implied IIS rates. Despite this being the market-standard approach proposed by the main info-providers, this methodology has important drawbacks from an econometric perspective.

In fact, it does not take into account basic indicators, such as R^2 or the absence of autocorrelation in the errors: it substantially repeats the same twelve-monthly residuals over time, as shown in Fig. 4.
The black line represents the historical CPI log-returns and the red one shows their projections in accordance with the standard approach.

$\boldsymbol{T_M}$	$\boldsymbol{K(T_M)}$ [%]	$\boldsymbol{\mathfrak{I}_M(0)}$	$\boldsymbol{\Delta\mathfrak{I}_M}$ [%]
1	1.206	105.8010	0.0999
2	1.010	106.6624	0.0676
3	0.966	107.5989	0.0729
4	0.972	108.6642	0.0821
5	1.003	109.8862	0.0932
6	1.034	111.1986	0.0989
7	1.055	112.5090	0.0976
8	1.081	113.9302	0.1046
9	1.111	115.4697	0.1119
10	1.133	117.0034	0.1100

Table 1. Mid Price $\boldsymbol{K(T_M)}$,$\boldsymbol{\mathfrak{I}_M(0)}$ and $\boldsymbol{\Delta\mathfrak{I}_M}$ (Market Data: 31st December 2020)

Month (M)	Standard Approach [%]	LSTM-Method I [%]
January (1)	-1.198	-0.761
February (2)	0.174	-0.018
March (3)	0.836	0.575
April (4)	0.264	0.292
May (5)	0.081	0.019
June (6)	0.086	0.009
July (7)	-0.529	-0.272
August (8)	-0.027	-0.375
September (9)	0.246	0.339
October (10)	0.111	0.188
November (11)	-0.219	-0.105
December (12)	0.175	0.108

Table 2. Historical Normalized residuals, $\boldsymbol{\mathfrak{R}_M}$, in accordance with the standard methodology (Market Data: 12/31/2020)

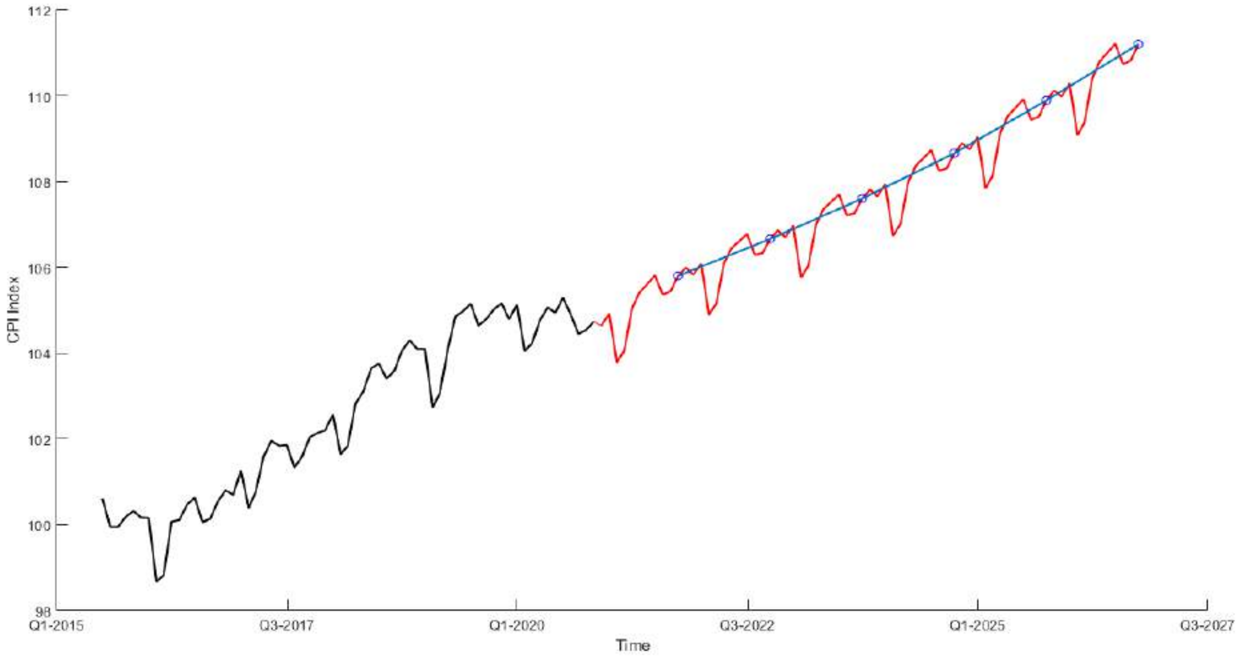

Figure 3. CPI time series and its projection (standard methodology)

The idea is to improve the seasonality model using a method with the following characteristics:
A) it is reliable from an econometric and statistical perspective
B) it is able to deal with potentially high non-linearities recorded by the financial series.
C) it takes into account market information (ZCIIS rates) and, consequently, it is aligned with traditional quantitative finance market best-practice (see paragraph 2).

With these objectives in mind, we design a Long Short-Term Memory (LSTM) network with the characteristics illustrated in paragraph 4. For the training set, we use the monthly return of the index computed in the last 5 years: $\ln\left[\frac{\Im_{i+1}^{Monthly}}{\Im_{i}^{Monthly}}\right]$. The number of hidden units in the LSTM block is tuned in function of the performances recorded by the network. Using a layer made of 100 neurons, adopting an ADAM optimizer and implementing a drop-out technique in order to avoid overfitting we can achieve excellent results in the training phase (de Simon-Martin et al., 2020). From a statistical point of view, as shown in Fig. 5, we obtain a high R^2, meaning that the fitting over the historical time series can be considered extremely good. From an econometric point of view, Fig. 6 shows that the auto-correlation in the errors for the tuned model has been kept, with a confidence interval equal to 95%, under an acceptable threshold (represented in red dotted lines) for the non-zero lags (Tsay, 2010).

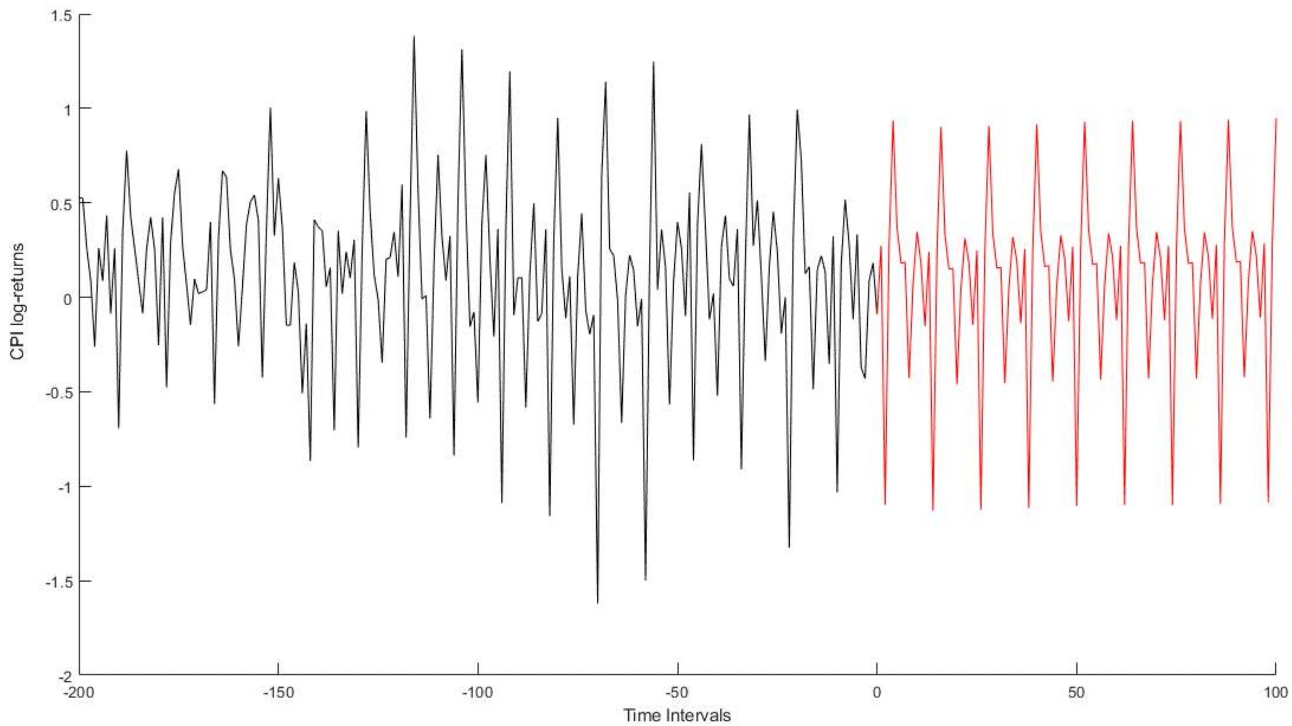

Figure 4. Historical and perspective estimation for seasonality using standard methodology

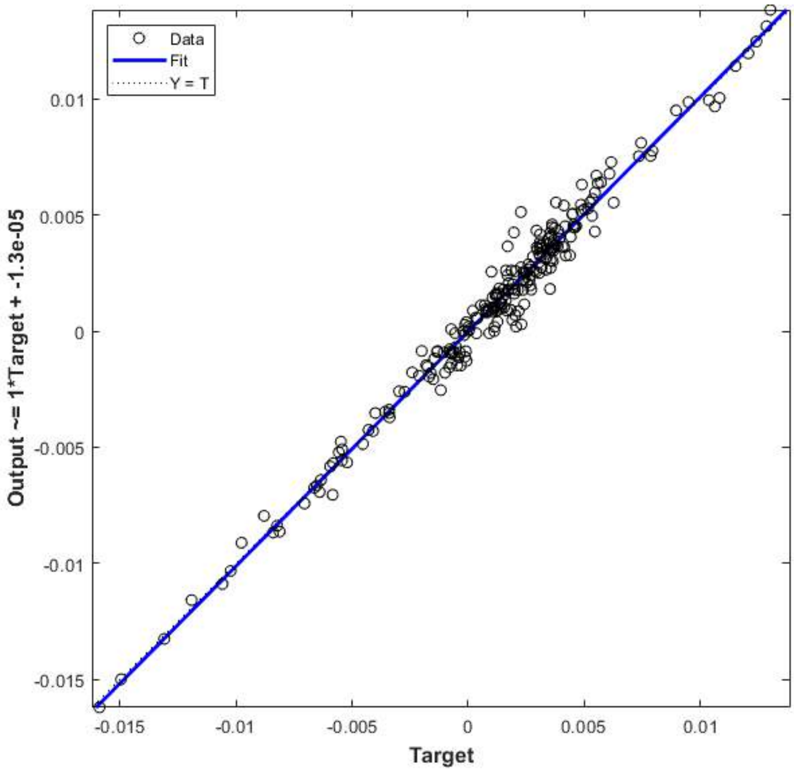

Figure 5. Regression plot for the LSTM network. $\boldsymbol{R^2} = \mathbf{0.98}$

Having checked the reliability of the LSTM network through statistical and econometric test, we proceed to make the CPI forecasts. Facing the forecasting problem with the Deep Learning approach, the projections have a more realistic forward-looking behavior thanks to both the advanced technology (deep learning) and the careful tuning as shown in Figure 7.

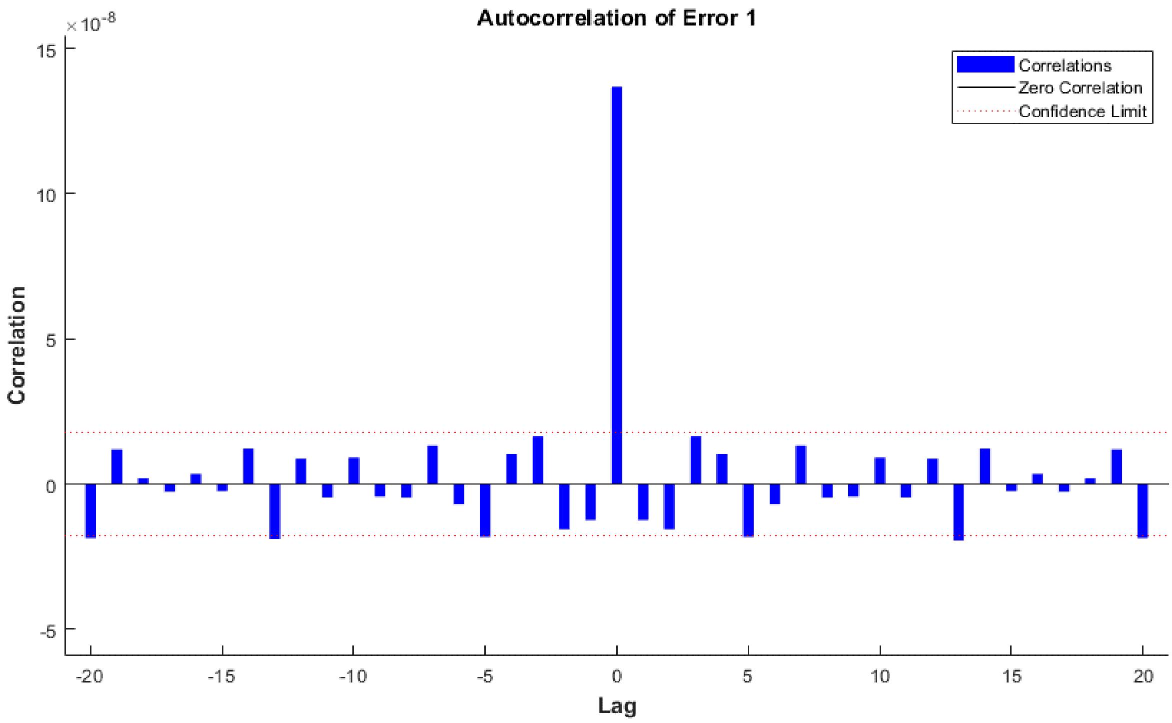

Figure 6. Auto-correlation error for LSTM network

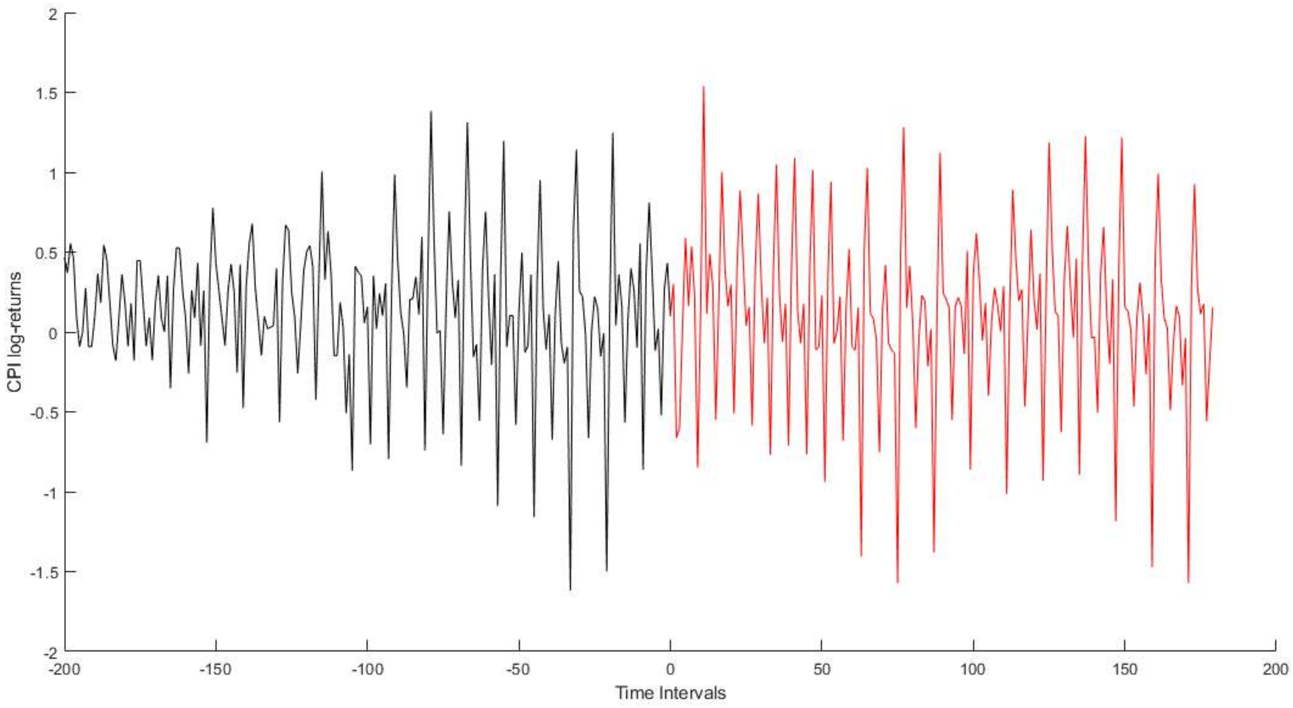

Figure 7. Historical and perspective estimation for seasonality using the Deep Learning methodology

Performing these seasonality projections guarantees to be compliant with points A) and B) of the desired requirements but not with the last one. In fact the log-returns projections cannot be used as-is in the pricing framework because they do not pass through the market-implied future values (see Table 1). Starting from these LSTM projections, two approaches can be followed in order to take into consideration this quantitative finance aspect:

LSTM-Method I) determines the monthly standardized residuals along the overall forecasted values.

LSTM-Method II) determines the monthly standardized residuals among the time intervals delimited by the market-implied rates.

LSTM-Method I) does not introduce an innovative idea with respect to the standard method with the difference that this is applied to the forecasted CPI values instead of using the historical values. It is substantially a forward-looking standard method. The twelve standardized residuals are reported in the third column of Table 2.

LSTM-Method II) applies the normalization of future residuals not on the entire forecasted horizon, but it considers the projected values for the computation among the time intervals delimited by the market-implied rates. This approach is less similar to the traditional one but it allows a more precise CPI seasonality projection in which the constrained C) remains satisfied. For this reason, we believe that the second approach has to be preferred.

LSTM-Method I) does not change the iterative formula (26) for $\mathfrak{I}$ because the seasonality term remains constant over the years and it can assume only twelve values, as reported in Table 2. The main difference between the standard methodology and this approach is a different estimation of the normalized residuals: the former considers the previous five years of the CPI values (as a result it is a backward-looking method), while the latter improves the forecasting, considering the projected five years values (as a result it is a forward-looking method). Despite this improvement, it remains a static technique.

LSTM-Method II) does not only introduce a forward-looking view, but also adds a more interesting contribution in terms of dynamics. In this second case the formula (26) slightly changes, because of the insertion of an index j that allows to clarify the exact contribution of $\boldsymbol{\mathfrak{R}_M^j}$ in connection with the cluster it belongs to. This happens because it changes between the time intervals defined by the listed ZCIIS ($\boldsymbol{j = 1, \ldots, T_M}$).

6) Robust check of the LSTM results

One of the main problems associated with dynamics neural networks for forecasting is that they are able to provide only projections without their related confidence intervals. This is mainly due to the fact that they are able to learn highly non-linear predictions in a time series without the need to make any assumptions regarding statistical distributions.

This is certainly a strength for capturing non-standard relationships, but it does not allow the analyst to express the results in terms of confidence bands. In order to improve the readability of the LSTM results and, consequently, help the user to be confident on the projection made by the network, we design a traditional econometric Seasonality ARIMA model (SARIMA). The model is an ARIMA(p,d,q) error model seasonally integrated with Seasonal MA(12). We maintain the seasonality effect equal to one year, that is 12 lags and we implement the traditional Gaussian distribution.

The main idea is to be able to calculate the confidence intervals for the econometric models at 5% and 95% using percentiles method in a Monte Carlo method based on the SARIMA and comparing these extreme values with the LSTM point predictions. This comparison can help the analyst to understand if the simulated seasonality can be reasonable. This comparisons between innovative (and maybe black-box) methodologies and traditional statistical models are more and more widespread in the Explainable Artificial Intelligence.

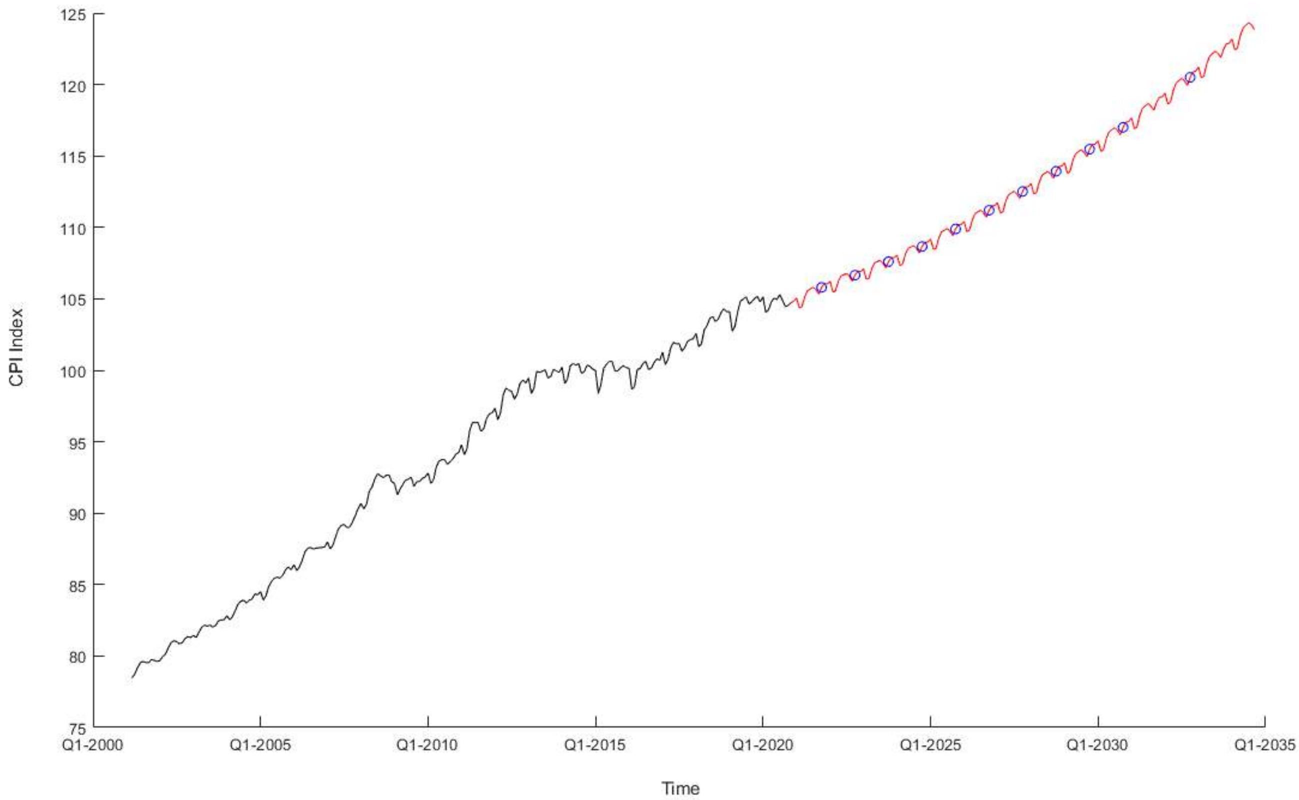

Figure 8. CPI time series and its projection (LSTM-Method I)

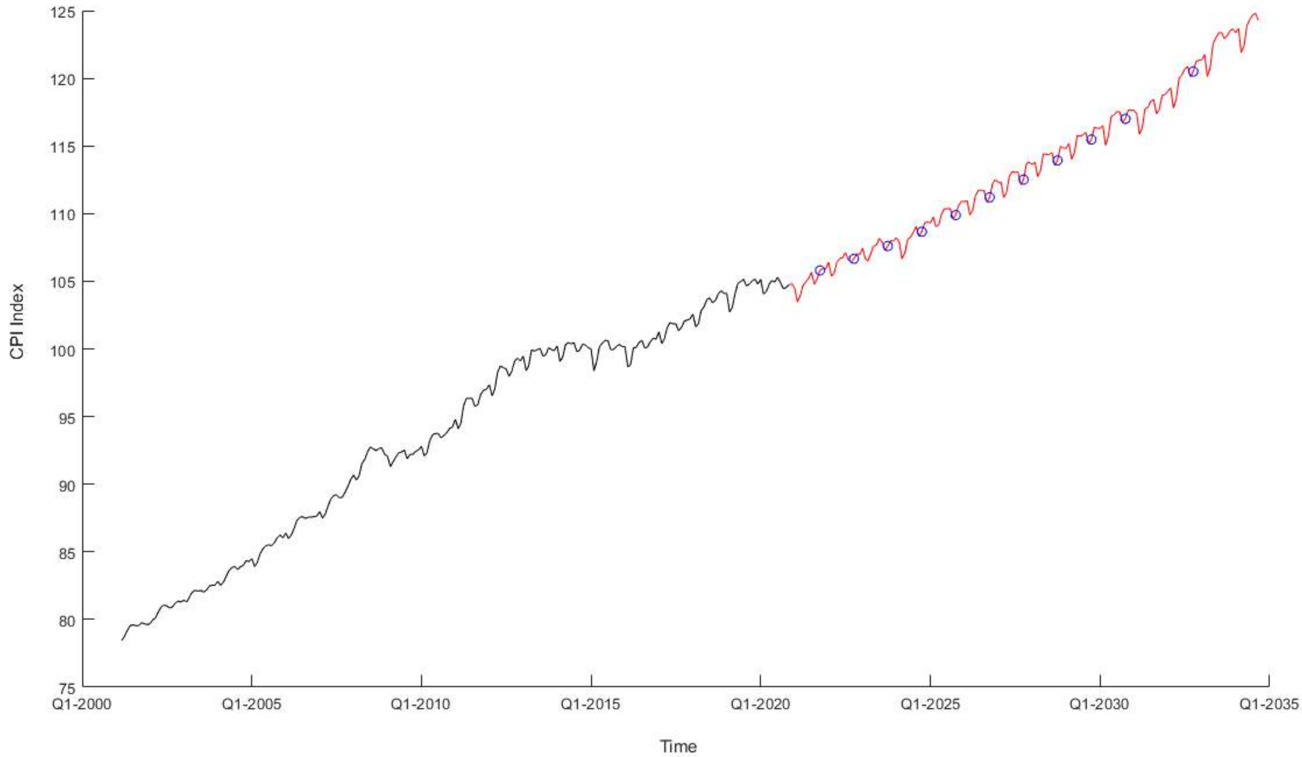

Figure 9. CPI time series and its projection (LSTM-Method II)

The first step is to choose the order for our Seasonal ARIMA(p,d,q) model that is find the best p, d and q parameters. With this aim we generate two tensors in which we store the Akaike's Information Criterion (AIC) and the Bayesian Information Criteria (BIC) estimated iteratively for all possible sets of parameters: $p = 1, \dots ,5$, $d = 1, \dots ,5$ and $q = 1, \dots ,5$. The minimum AIC and BIC is for a SARIMA(1,1,2). The second step is to find the estimation of the model and then perform 100,000 simulations for the next months (i.e.120) for computing the 5% and 95% in correspondence of these time steps. Figure 10 highlights that the empirical confidence intervals of the traditional econometric SARIMA model (red lines) include almost all the LSTM network predictions (blue lines). This information can help the analyst to understand that the Machine Learning produce reasonable predictions because its outputs stay inside the extreme forecasts done with a methodology for which confidence bands can be estimated.

This helps to reduce the black-box effect and consequently to better explain the outcomes of the deep learning methodology.

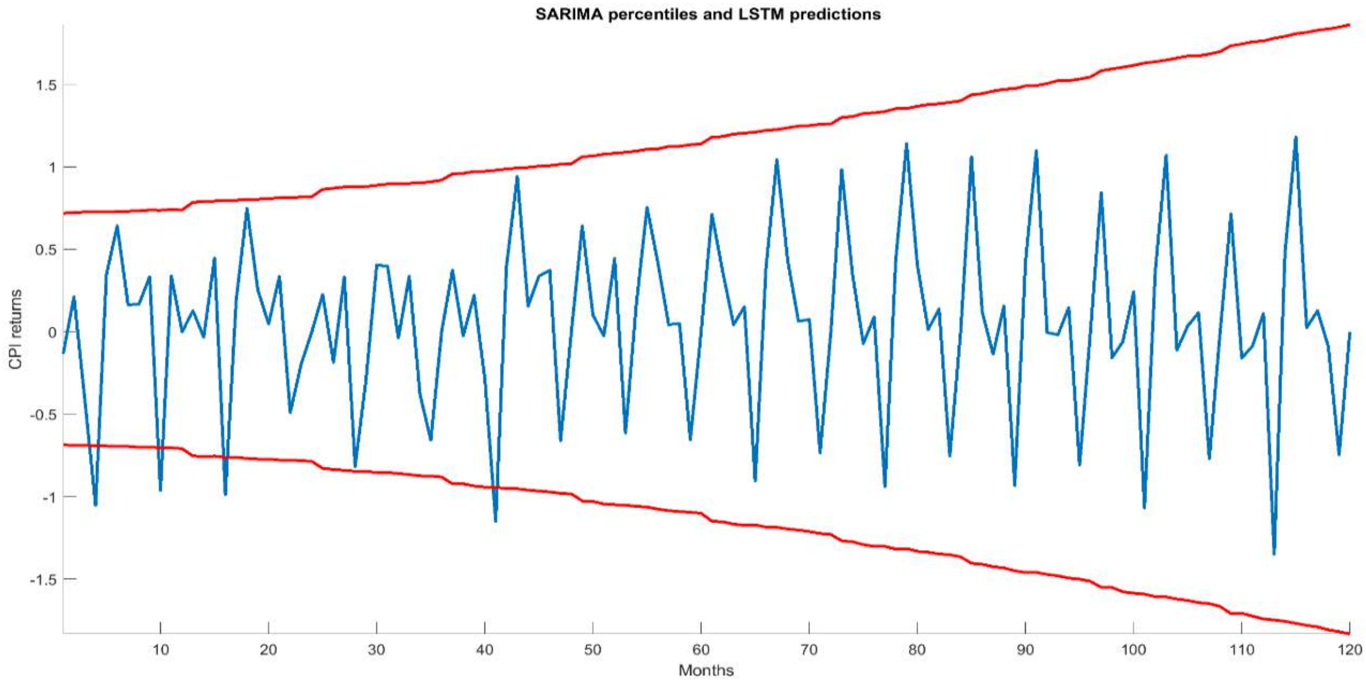

Figure 10. SARIMA(1,1,2) with Seasonal lag equal to 12 percentiles and the LSTM projection

7) Market Case: YYIIS pricing

The seasonality model obviously has an impact on the derivative fair-value that is not always negligible.
In this paragraph, we proceed with the valorization of a YYIIS swap using the two approaches described in the previous paragraphs. The main financial characteristics are reported in Table 3.
The valuation date of the "In Arrears" swap is 31st December 2020, thus we can use the historical and prospective inflation data already computed in the previous paragraphs. Regarding the discount curve we use, according to the new benchmark standard for collateralized derivatives is the EUR OIS ESTR term structure.
As a result, zero rates and discount factors used for pricing are those implied from the new market benchmark curve (see Table 4).

YOY Swap	Receiving Leg	Paying Leg
Leg Type	Y-o-Y Inflation	Fixed
Notional	10 MM	10 MM
Currency	Euro	Euro
Index	CPTFEMU Index	Fixed Coupon: 2.1%
Effective Date	31st Dec. 2010	31st Dec. 2010
Maturity Date	31st Dec. 2030	31st Dec. 2030
Lag	3 Month	-
Interpolation	Monthly	-
Spread	0	-
Reset Frequency	Semi-Annual	-
Payment Freq.	Semi-Annual	Annual
Day Count	ACT/360	ACT/ACT
Discount Curve	EUR-OIS-ESTR	EUR-OIS-ESTR

Table 3. Year-on-Year Inflation Indexed Swap Financial Characteristics

Term	Market Rates	Zero Rates	Discount Factors
1 DY	-0.583	-0.5911	1.000016
1 WK	-0.555	-0.56274	1.000108
2 WK	-0.555	-0.56277	1.000216
1 MO	-0.5245	-0.5319	1.000452
2 MO	-0.56	-0.56804	1.000919
3 MO	-0.564	-0.57224	1.001428
4 MO	-0.5685	-0.57694	1.001899
5 MO	-0.5703	-0.57892	1.00243
6 MO	-0.574	-0.58281	1.002894
7 MO	-0.5778	-0.58682	1.003414
8 MO	-0.581	-0.59023	1.003953
9 MO	-0.586	-0.59546	1.004464
10 MO	-0.5875	-0.59714	1.004986
11 MO	-0.5895	-0.59933	1.005516
12 MO	-0.592	-0.60203	1.006038
18 MO	-0.602	-0.61189	1.009195
2 YR	-0.61262	-0.61446	1.012365
3 YR	-0.60932	-0.61118	1.018504
4 YR	-0.60118	-0.60266	1.024433
5 YR	-0.58329	-0.58494	1.029695
6 YR	-0.55663	-0.55851	1.034094
7 YR	-0.5222	-0.52437	1.037402
8 YR	-0.48456	-0.48686	1.039745
9 YR	-0.44388	-0.4465	1.041054
10 YR	-0.39831	-0.40124	1.040974

Table 4. EUR-OIS-ESTR Discount Curve. Reference Date: 31st December 2020. Source: Bloomberg®

Using the pricing formulas derived in paragraph 2, we proceed with the estimation of the future cash-flows for the swap and then we go through the discounting process for obtaining the NPVs for the two legs. The difference between the two NPVs gives the price of the swap. In detail:

- the discounted Cash Flows for the fixed paying leg of the swap are equal to -2,159,760.13 Euro (see Table 5).
- the discounted Cash Flows for the inflation-indexed receiving leg of the swap using the standard seasonality approach are equal to +1,178,818.67 Euro (see Table 6).
- the discounted Cash Flows for the inflation-indexed receiving leg of the swap using the deep learning architecture are equal to +1,231,750.60 Euro (see Table 7).

Accrual Start	Payment Date	Days	Notional	Coupon	Payment	Discount	Zero Rate	PV
12/31/2020	12/31/2021	365	-10000000	2.1	-209998.43	1.006032	-0.60144	-211265.24
12/31/2021	12/30/2022	364	-10000000	2.1	-209424.66	1.012343	-0.61422	-212009.62
12/30/2022	12/29/2023	364	-10000000	2.1	-209424.66	1.018469	-0.61115	-213292.62
12/29/2023	12/31/2024	368	-10000000	2.1	-211152.26	1.02442	-0.60276	-216308.66
12/31/2024	12/31/2025	365	-10000000	2.1	-209998.43	1.029709	-0.5852	-216237.26
12/31/2025	12/31/2026	365	-10000000	2.1	-210000.00	1.034121	-0.55895	-217165.47
12/31/2026	12/31/2027	365	-10000000	2.1	-210000.00	1.037446	-0.52497	-217863.67
12/31/2027	12/29/2028	364	-10000000	2.1	-208854.03	1.039792	-0.48775	-217164.65
12/29/2028	12/31/2029	367	-10000000	2.1	-211145.97	1.041122	-0.44749	-219828.70
12/31/2029	12/31/2030	365	-10000000	2.1	-210000.00	1.041068	-0.40225	-218624.24

Table 5. Fixed Payment Leg Valuation

Accrual Start	Accrual End	Days	Notional	Reset Date	Reset Rate	Reset Price	Coupon	Payment	Discount	Zero Rate	PV
12/31/2020	06/30/2021	181	10000000	03/01/2021	0.6337	104.86851	0.6337	31860.78	1.002892	-0.582367	31952.92
06/30/2021	12/31/2021	184	10000000	09/01/2021	1.76383	**105.80096**	1.76383	90151.2	1.006032	-0.601438	90695.04
12/31/2021	06/30/2022	181	10000000	03/01/2022	0.52997	106.07902	0.52997	26645.85	1.009188	-0.611429	26890.68
06/30/2022	12/30/2022	183	10000000	09/01/2022	1.09685	**106.66237**	1.09685	55756.46	1.012343	-0.614222	56444.67
12/30/2022	06/30/2023	182	10000000	03/01/2023	0.59075	106.97656	0.59075	29865.85	1.015412	-0.612777	30326.13
06/30/2023	12/29/2023	182	10000000	09/01/2023	1.16675	**107.59893**	1.16675	58985.67	1.018469	-0.611149	60075.11
12/29/2023	06/28/2024	182	10000000	03/01/2024	0.70232	107.97574	0.70233	35506.43	1.021433	-0.607088	36267.44
06/28/2024	12/31/2024	186	10000000	09/01/2024	1.25114	**108.66416**	1.25114	64642.41	1.02442	-0.60276	66221
12/31/2024	06/30/2025	181	10000000	03/01/2025	0.84101	109.11734	0.84101	42283.91	1.02709	-0.59417	43429.38
06/30/2025	12/31/2025	184	10000000	09/01/2025	1.39773	**109.88619**	1.39773	71439.3	1.029709	-0.585203	73561.69
12/31/2025	06/30/2026	181	10000000	03/01/2026	0.90813	110.38104	0.90813	45658.9	1.031968	-0.572289	47118.54
06/30/2026	12/31/2026	184	10000000	09/01/2026	1.46395	**111.19565**	1.46395	74823.95	1.034121	-0.558946	77377.04
12/31/2026	06/30/2027	181	10000000	03/01/2027	0.89757	111.69057	0.89757	45127.69	1.035863	-0.542196	46746.12
06/30/2027	12/31/2027	184	10000000	09/01/2027	1.45352	**112.50897**	1.45352	74291.22	1.037446	-0.524965	77073.13
12/31/2027	06/30/2028	182	10000000	03/01/2028	0.97434	113.05558	0.97434	49258.37	1.038719	-0.50642	51165.62
06/30/2028	12/29/2028	182	10000000	09/01/2028	1.55144	**113.93017**	1.55144	78433.73	1.039792	-0.487753	81554.73
12/29/2028	06/29/2029	182	10000000	03/01/2029	1.06202	114.53349	1.06202	53690.98	1.040562	-0.467854	55868.81
06/29/2029	12/31/2029	185	10000000	09/01/2029	1.61278	**115.46973**	1.61278	82879.04	1.041122	-0.447493	86287.18
12/31/2029	06/28/2030	179	10000000	03/01/2030	1.05645	116.06797	1.05645	52528.81	1.041221	-0.425386	54694.11
06/28/2030	12/31/2030	186	10000000	09/01/2030	1.58155	**117.00341**	1.58155	81713.54	1.041068	-0.402249	85069.33

Table 6. Inflation-Indexed Receiving Leg Valuation using the standard approach

Accrual Start	Accrual End	Days	Notional	Reset Date	Reset Rate	Reset Price	Coupon	Payment	Discount	Zero Rate	PV
12/31/2020	06/30/2021	181	10000000	03/01/2021	0.28164	104.68732	0.28164	14160.14	1.002892	-0.582367	14201.09
06/30/2021	12/31/2021	184	10000000	09/01/2021	2.11633	**105.80096**	2.11633	108167.9	1.006032	-0.601438	108820.38
12/31/2021	06/30/2022	181	10000000	03/01/2022	1.12420	106.39734	1.12420	56522.2	1.009188	-0.611429	57041.53
06/30/2022	12/30/2022	183	10000000	09/01/2022	0.49757	**106.66237**	0.49757	25293.1	1.012343	-0.614222	25605.29
12/30/2022	06/30/2023	182	10000000	03/01/2023	0.71823	107.04610	0.71823	36310.58	1.015412	-0.612777	36870.20
06/30/2023	12/29/2023	182	10000000	09/01/2023	1.03022	**107.59893**	1.03022	52083.28	1.018469	-0.611149	53045.21
12/29/2023	06/28/2024	182	10000000	03/01/2024	-0.95952	107.08395	-0.95952	-48509.1	1.021433	-0.607088	0.00
06/28/2024	12/31/2024	186	10000000	09/01/2024	2.92979	**108.66416**	2.92979	151372.4	1.02442	-0.60276	155068.92
12/31/2024	06/30/2025	181	10000000	03/01/2025	0.91998	109.16515	0.91998	46254.4	1.02709	-0.59417	47507.44
06/30/2025	12/31/2025	184	10000000	09/01/2025	1.31665	**109.88619**	1.31665	67295.66	1.029709	-0.585203	69294.94
12/31/2025	06/30/2026	181	10000000	03/01/2026	0.65143	110.24469	0.65143	32752.3	1.031968	-0.572289	33799.33
06/30/2026	12/31/2026	184	10000000	09/01/2026	1.72312	**111.19862**	1.72312	88070.79	1.034121	-0.558946	91075.85
12/31/2026	06/30/2027	181	10000000	03/01/2027	0.66842	111.57088	0.66842	33606.8	1.035863	-0.542196	34812.04
06/30/2027	12/31/2027	184	10000000	09/01/2027	1.67458	**112.50897**	1.67458	85589.4	1.037446	-0.524965	88794.38
12/31/2027	06/30/2028	182	10000000	03/01/2028	1.19056	113.18071	1.19056	60189.29	1.038719	-0.50642	62519.76
06/30/2028	12/29/2028	182	10000000	09/01/2028	1.31999	**113.93017**	1.31999	66733.04	1.039792	-0.487753	69388.48
12/29/2028	06/29/2029	182	10000000	03/01/2029	0.97715	114.48816	0.97715	49400.22	1.040562	-0.467854	51403.99
06/29/2029	12/31/2029	185	10000000	09/01/2029	1.70740	**115.46973**	1.70740	87741.21	1.041122	-0.447493	91349.31
12/31/2029	06/28/2030	179	10000000	03/01/2030	0.39262	115.69663	0.39262	19521.73	1.041221	-0.425386	20326.44
06/28/2030	12/31/2030	186	10000000	09/01/2030	2.24632	**117.00341**	2.24632	116059.7	1.041068	-0.402249	120826.04

Table 7. Inflation-Indexed Receiving Leg Valuation using the LSTM approach

The gap between the values from the two pricing methodologies is equal to -52,931.93 and, consequently, the percentage error, measured as the ratio between the absolute evaluation discrepancy and the notional of the derivative, is higher than 0.529%.

It is worth noting that the simulated future CPIs implied by the rates of the listed ZCIIS are exactly the same independently of the implemented seasonality method (i.e. standard or LSTM-Method 2). These values are highlighted in bold in Tables 6 and 7.

LSTM-Method I) provides a result very close to the standard methodology: the NPV of the inflation-indexed receiving leg is 1,175,808.67 Euro.

8) Conclusions

This study shows how a Deep Learning methodology can be usefully implemented in a pricing framework, aiming at determining the fair value of derivatives linked to the inflation index.

The Long Short-Term Memory Network allows to identify the effect of seasonality in a more reliable way compared to traditional methodologies. In fact, the proposed technique is able to simulate the future values of the time series by applying the described rigorous statistical and econometric tests, reasonably guaranteeing the reliability of the forecasts.

On the contrary, the traditional approach, based on the estimation of the historical normalized residuals, does not consider these important tests and it is not able to capture highly nonlinear relationships as a LSTM network does. It is particularly interesting considering how artificial intelligence paradigms can be integrated with traditional pricing methodologies in the field of quantitative finance.

In summary, the study shows that seasonality has larger impacts than previously expected on the Inflation-Indexed Swaps valuation, especially when counterparties exchange a fixed interest rate compared to a floating rate.

The proposed methodology also combines market elements with a machine learning approach, making the method more dynamic, despite inflation rates being estimated only periodically.

In addition, thanks to this dynamic approach, the model proposed allows financial institutions to better estimate future cash flows that counterparties have to exchange over the years, so to make the risk management process more accurate compared to more traditional approaches.

Despite the results being interesting, this research represents only a preliminary study in this area and further analyses to test and to improve the model are thus required.

Possible future researches could aim either at determining which factors impact the most on the variability of the results, or at seeing the implications of such methodology when applied to derivative contracts, written on underlyings (such as commodity and energy derivatives) where the seasonality effect is of fundamental importance.

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