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Integrating Solvency and Liquidity Stress Tests: The Use of Markov Regime-Switching Models

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Integrating Solvency and Liquidity Stress Tests: The Use of Markov Regime-Switching Models

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Abstract

The paper presents a framework to integrate liquidity and solvency stress tests. An empirical study based on European bond trading data finds that asset sales haircuts depend on the total amount of assets sold and general liquidity conditions in the market. To account for variations in market liquidity, the study uses Markov regime-switching models and links haircuts with market volatility and the amount of securities sold by banks. The framework is accompanied by a Matlab program and an Excel-based tool, which allow the calculations to be replicated for any type of traded security and to be used for liquidity and solvency stress testing.

JEL Classification Numbers: G12, G21, G32

Keywords: stress testing, solvency risk, liquidity risk, asset fire sales, Markov regime-switching models

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Glossary

AE	Asset Encumbrance
BIS	Bank for International Settlements
BP	Basis Point
CAR	Capital Adequacy Ratio
CBC	Counterbalancing Capacity
CCP	Central Clearing Counterparty
CET1	Core Equity Tier 1 Capital Ratio
CUSIP	Committee on Uniform Security Identification Procedures
DSGE	Dynamic Stochastic General Equilibrium
ELA	Emergency Liquidity Assistancy
ESRB	European Systemic Risk Board
FSAP	Financial Sector Assessment Program
FSB	Financial Stability Board
FX	Foreign Exchange
GFC	Global Financial Crisis
G-SIB	Global Systemically Important Bank
IMF	International Monetary Fund
ISIN	International Security Identification Number
LIBOR	London Interbank Offered Rate
MLP	Market Liquidity Premium
MTS	MTS Markets (company)
OFR	Office of Financial Research
RWA	Risk-Weighted Asset
SFT	Securities Financing Transaction
TARP	Troubled Asset Relief Program
UK	United Kingdom
US	United States
VIX	Chicago Board of Trade Volatility Index
VWAP	Volume-Weighted Average Price

I. Background

Interaction of solvency and liquidity risks in the financial system is an important driver of the severity of crises: solvent financial institutions[2] may be forced to liquidate assets, face losses, and become insolvent. The feedback loops between solvency and liquidity risks could amplify capital losses and lead to liquidity problems during stress episodes (Adrian and Shin 2010; BCBS 2015). A stress tester needs to take into account that banks that face higher solvency risks in adverse scenarios are also likely to experience higher funding costs and tighter funding liquidity conditions. In addition, funding withdrawals could also lead to further liquidity shortages and liquidation of assets to cover negative funding gaps. Such liquidation could undermine market liquidity conditions for the assets that are liquidated by many financial institutions altogether, and hence increase losses from the liquidation, further undermining capital positions. As seen during the Global Financial Crisis (GFC), asset fire sales produced a chain of contagion: many financial institutions in the United States (US) and Europe faced funding withdrawals; to meet demand for cash, those institutions had to sell assets priced below fundamental ones. Government interventions such as the Troubled Asset Relief Program (TARP) in the US and the broadening of collateral frameworks for central bank refinancing operations (euro area, Japan, United Kingdom [UK]) were able to stop the vicious circle of declines in prices, further withdrawals, and liquidity shortfalls.

Unprecedented intervention of the central banks in providing liquidity support to banks in the form of broadened collateral frameworks, which includes, inter alia, full allotment auctions as well as acceptance of high-quality credit claims as eligible collateral, shifted funding liquidity sources from market to central banks. Moreover, massive asset purchase programs increased market liquidity of sovereign and corporate bonds. Last but not least, secured funding (repos and reverse repos) started to dominate wholesale funding markets. These trends shifted structural liquidity risks away from funding to market liquidity, that is, systemic liquidity risk assessment needs to answer questions such as to what extent market liquidity of securities would be affected if central banks changed their accomodative policy course; and to what extent migration to secured funding would increase contingent liquidity risks?

The aim of this paper is to develop a practical tool to calculate dynamic haircuts for assets in a stylized banking system that broadly captures the solvency-liquidity feedback loops including changes in market liquidity premia. This paper takes an empirical approach (that is, the Markov regime-switching models for market liquidity) to linking haircuts with the volume of securities to be sold (both at the individual and banking system-wide level) under the given scenarios. The suggested approach does not require extensive parameter calibrations to estimate the market liquidity premia from asset fire sales under stress scenarios and uses historical daily trading data to estimate haircuts by type and maturity of

[2] We use the term "financial institutions" in cases when we talk about banks and all other non-bank institutions.

security. In the next step, haircuts are linked with liquidity stress tests to estimate system-wide amounts of securities sold, and finally are linked with solvency stress tests to estimate effects on capital via mark-to-market losses. The approach can be tailored to any security where historic daily trading data are available. Asset fire-sale models can also be used for counterfactual policy simulations to estimate implicit support banks would need to receive in case of crises. Further extension of the framework links haircuts with market volatility indexes (such as VIX), as these are good predictors of illiquidity episodes.

Public interventions also created a problem of moral hazard: to what extent public institutions should support banks and other private financial institutions and shield them from liquidity risk and/or help them to minimize losses? Expectations about public support helps banks to maximize returns by engaging in longer than socially optimal maturity transformation (that is, maximizing the amount of cheaper short-term borrowing) and investing in riskier assets, as well as having lower and less diversified liquidity buffers. While public interventions minimized the probability of asset fire sales per se, they did not eliminate the need to estimate potential liquidity risks due to extreme market events, because haircuts that central banks apply to assets are applied on top of market prices.

The problem of market liquidity is also important in emerging markets, where central banks are not able to buy large amounts of their own sovereign or corporate bonds denominated in foreign currencies because of limited foreign exchange reserves or buy bonds issued in domestic currency because of fear of inflation[3].

Hence, a stress tester needs to bear in mind market liquidity conditions under the stressed environment. In a typical liquidity stress-testing framework, many of the stress parameters are calibrated outside of the stress-testing framework itself, that is, liquidity risk is exogenously determined. Such tests assume constant haircut ratios—obtained from macro models, such as Dynamic Stochastic General Equilibrium (DSGE) with asset prices, or by looking into the past historic episodes; thus, haircuts are not linked with the amount of securities sold—for the liquidation of counterbalancing capacity (CBC) in the market to offset negative funding shocks (Jobst and others 2017). However, haircuts are closely linked with the market liquidity conditions in asset markets, which are endogenously determined, that is, they depend on distribution of asset holdings, amount of supply (sales), and demand. It is widely recognized (see, for example, IMF 2010; Houben and others 2015) that systemic liquidity is an endogenous concept, that is, it depends on risk tolerance among market participants as well as general macrofinancial conditions. Other studies (for example, ESRB 2016) identified the phenomenon of liquidity illusion—instruments liquid during normal times become illiquid during stress periods. While this suggests the binary concept of liquidity, that is, assets are either liquid or illiquid, in practice, it is difficult to estimate when a given security becomes completely illiquid, when no trade would be possible under any

[3] One of the most recent examples of bond market illiquidity would be turmoil in emerging markets at the beginning of 2018.

given price. In most of the stress tests, stress testers can assume that there are potential buyers for any security; however, the ask price should be well below the one observed under normal market conditions and/or the issuer's financial situation.

The rest of the paper is organized as follows. Section II reviews the major contributions in literature and identifies the remaining analytical challenges and gaps. Section III introduces a tool for the assessment of dynamic haircuts. Section IV presents an application of the methodology to sovereign bonds of selected euro area countries. Last, Section V concludes the paper and discusses possible future extensions.

II. Literature Review

Liquidity risk modeling is a part of banks' internal risk management process and supervisory assessment (the so-called "Internal Liquidity Adequacy Assessment Process"). Liquidity stress tests are also widely used in the context of IMF FSAPs. Liquidity risks are typically assessed by liquidity stress tests, which include a comprehensive calculation of whether banks' own internal resources (in the form of liquidity buffers) are sufficient to withstand adverse funding shocks[4]. Schmieder and others (2012) and Jobst and others (2017) provide a detailed description of liquidity stress-testing approaches. Two broad and mutually reinforcing types of liquidity risks are typically considered in liquidity stress tests:

- *Funding liquidity risk* is the risk that a bank will not be able to cover its current or future cash outflow in case of a runoff in its funding liabilities, contingent payment obligations, and/or disruptions to cash inflows. Shocks to funding liquidity could lead to higher runoff rates in key funding markets—both retail and wholesale—and higher funding costs in some cases. For liquidity stress tests, such runoff rates influence the severity of cash outflow calculations. More recently, funding liquidity risk has come less from retail deposit outflows and more from exposures to a range of lending and interbank financial arrangements and uninsured wholesale deposits. These include so-called contingent liquidity risks, such as undrawn loan commitments, obligations to repurchase securitized assets, margin calls in the derivatives markets, and withdrawal of funds from wholesale short-term financing arrangements.

- *Market liquidity risk* is the risk that a bank will not be able to buy or sell a sizeable volume of securities at a low cost and with a limited price impact (IMF 2015). The level of market liquidity has many aspects such as time, cost, and quantity, and most measures

[4] In the cash flow-based liquidity stress tests, which have been widely used in supervisory stress tests, it is assessed whether an individual bank's counterbalancing capacity (CBC)—bank assets available for liquidation to offset negative funding gaps—and expected cash inflows are adequate to cover expected cash outflows over a defined stress horizon. The gap between the former and the latter is typically called a funding gap. These tests would usually examine the resilience of individual banks without directly taking into account central banks' emergency liquidity assistance (ELA) as the lender of last resort (Jobst and others 2017). Hence, the size of the negative funding gaps can inform about potential liquidity needs of banks and the amount of potential asset liquidation. It can also imply the potential amount for ELA from central banks in periods of stress.

of market liquidity only capture one aspect. For example, the bid-ask spreads, price impact measures, and imputed "round-trip" costs can capture the cost dimension. Since the level of market liquidity is prone to sudden dry-up, a significant component of market liquidity risk is the resilience of market liquidity, or in other words, how likely is market liquidity prone to a sudden dry-up (Brunnermeier and Pederson 2009; IMF 2015). Acharya and others (2013), IMF (2015), and Flood and others (2015) also found that market liquidity tends to exhibit a regime-switching behavior, wherein one regime the level of market liquidity is high, but in the other it evaporates rapidly. For liquidity (and partly also solvency) stress tests, banks assess the expected cash inflows from asset liquidation and secured funding in a stressed environment. Hence, assumptions about the decline in asset values and the extent to which assets are subject to haircuts when used as collateral for wholesale funding, affect the calculations of CBC and cash flows (Jobst 2017).

The interlinkages between funding and market liquidity risks can reinforce each other, leading to the so-called "liquidity spirals": margin calls (additional liquid assets provided to counterparties) and loss spirals (realized and unrealized [marked-to-market] losses due to a decline in market prices of assets). When speculators hit their capital constraints during stress periods, any negative funding shock could force speculators to reduce their positions, triggering a price drop—away from fundamentals—and a lower market liquidity. This is the margin sprial (Brunnermeirer and Pederson 2009) observed during the GFC, when margins and haircuts widened significantly (IMF 2007). Consistent evidence was also found by Adrian and Shin (2009) for investment banks. Market illiquidity could lead to losses in initial positions for speculators, tightening their funding constraint and forcing them to sell more. This is the loss spiral (Brunnermeirer and Pederson 2009). Moreover, market illiquidity is often associated with higher funding costs, which may create pressures on solvency. For example, foreign exchange (FX) swap costs increased substantially when the liquidity in the FX swap markets dried up in late 2007 for European banks seeking US dollar funding as a result of concerns over counterparty credit risk (IMF 2008). Liquidity spirals affect market prices, and the stress tester needs to quantify the potential impact of the amount of sales on security prices under different market liquidity regimes.

Asset fire-sale models help to shed light on market pricing of securities under stress. Pulvino (1998) analyzes commercial aircraft transactions and finds evidence that capital constrained airlines receive lower prices for their aircraft compared to unconstrained ones. Schleifer and Vishny (2010) provide an overview of fire-sales theory and potential policy interventions.

Fire-sales theory relies heavily on assumptions about information asymetry, as well as funding liquidity and capital constraints faced by both buyers and sellers. Some assets are marketable and easier to value, such as stocks and government bonds, while others are very specific and non-marketable, such as collateralized debt and complex products. In the case of relatively opaque non-marketable assets, buyers that have no or limited liquidity constraints would be buying assets at the valuations significantly below the fundamental prices. In the case of marketable assets (such as government and large corporate bonds and widely traded equities), fire sales would not happen if there were enough buyers without liquidity or capital constrains; and vice versa, capital/liquidity shortage in the financial system as well as failures of arbitrage (inefficient pricing due to information asymmetry) in financial markets would lead to fire-sale spirals (Figure 1)[5]. Brunnermeier and Pedersen (2009) as well as Adrian and others (2017) also found that market liquidity depends on balance-sheet conditions of liquidity providers (for example, their capital adequacy, leverage, access to funding markets, etcetera)[6].

Figure 1. Fire Sales, Asset Types, and Liquidity Constraints

		Seller (Supply)			
		No liquidity/capital constraints		**Liquidity/capital constraints**	
		Marketable assets	**Non-marketable assets**	**Marketable assets**	**Non-marketable assets**
Buyer (Demand)	**No liquidity/capital constraints**	No fire sale of assets occurs.	No fire sale of assets occurs.	No fire sale of assets occurs.	Fire sale of assets occurs.
	Liquidity/capital constraints	No fire sale of assets occurs.	No fire sale of assets occurs.	Fire sale of assets occurs.	Fire sale of assets occurs.

Source: Authors.

Empirical models were developed in recent years to characterize asset fire sales and the behavior of market liquidity, but to our best knowledge, there are limited studies that integrate liquidity risks with solvency risk in a practical and easy-to-use framework for stress testing. The stress tests developed by the Bank of Canada consider the rollover risks determined by expectations of insolvency and interbank contagion amplified by capital

[5] This raises the question of whether under expanded collateral frameworks (for example, euro area, Japan), fire sales of assets might still occur in the financial system. Episodes when central banks were reluctant to provide liquidity support to seemingly insolvent banks are mostly gone: secured funding (against eligible collateral) is provided to all eligible counterparts; hence, banks do not need to sell assets in the market to obtain liquidity. But what about non-bank financial institutions, such as mutual funds and hedge funds, insurance companies, and pension funds? Highly leveraged institutions face liquidity shortages under market-wide or idiosyncratic stress conditions; however, banks might be able to help to buy the assets (if they do not face liquidity constraints themselves). The role of the central banks changed the landscape for assets that are transparent (for example, Level 1) and thus can remain liquid even during a systemic crisis. At the same time, opaque financial products do pose a liquidity risk to the financial system.

[6] BCBS (2017a) finds that banks' capital ratios and the amount of Level 3 (specific) assets in their balance sheets are negatively correlated. This study finds that market contagion (through fair value pricing of assets) was not the dominant factor in contagion among the largest banks; contrary exposure to the same risk factors and uncertainty related to pricing of portfolio investments was the key. Since Level 2 and Level 3 assets are priced using rarely observed or unobserved inputs, their prevalence in balance sheets may lead to heightened liquidity and thus fire-sale risks for institutions that hold large amounts of these assets.

shortfalls (Anand and others 2014). The European Central Bank takes into account the interlinkages through funding costs and collateral values. The Oesterreichische Nationalbank models funding cost shock and losses on marketable securities, which feed into solvency stress tests, and the Bank of Korea's model captures the linkage that a drop in capital ratio (solvency risk) triggers liquidity runoffs (BCBS 2015). However, the interactions between deleveraging or asset fire sales and asset prices through deteriorated market liquidity conditions in a systemic event are not fully captured in these models. Barnhill and Schumacher (2011) analyzed correlated market and credit risks and estimated the probability that multiple banks will fail or experience liquidity runs simultaneously, but did not capture the funding cost channel.

The liquidity spirals are also not captured by simple implied or actual cash flow based liquidity stress tests. These liquidity stress tests assume constant haircut ratios for the liquidation of CBC in the market to offset negative funding shocks (Jobst and others 2017). Haircuts are endogenously linked with the market liquidity conditions in asset markets through the liquidity spirals and the nature of shocks (systemwide versus idiosyncratic). If idiosyncratic funding shock hits a small bank, then the liquidation of CBC by that bank is unlikely to have a large impact on market prices, implying a very small haircut. However, if the funding shock is systemwide, then the liquidation of the CBC by multiple banks should have a sizable impact on asset prices, depending also on the market liquidity regime and the amount of assets offered.

Modeling a stressed market liquidity premium (MLP) is a practical way to integrate solvency and liquidity risks. MLP measures interaction between market liquidity conditions and the impact of asset sales on asset prices[7]. Studies such as Iachini and Nobili (2014) focus on time-varying cross-correlation to identify abrupt changes in correlation among returns of multiple assets. Acharya and others (2013), IMF (2015), and Flood and others (2015) used Markov regime-switching models to characterize the regime-switching behavior of market liquidity in US corporate bond market, as liquidity is prone to suddenly drying up. Baranova and others (2017b) developed a partial-equilibrium model for dealer intermediation in the UK bond market to estimate the market liquidity premia and the impact on banks' liquidity and solvency buffers; the model was recently incorporated into the Bank of England's stress-testing framework (Baranova and others 2017a). However, complex models depend on multiple parameters to be calibrated, and this could be a difficult task for many countries due to data limitations. Similarly, another fire-sales model developed by Aikman and others (2009) captures interactions between funding and market liquidity risks; a similar approach was employed by Barnhill and Schumacher (2011). However, calibration of the parameters in

[7] "Market liquidity" is defined as the ability to rapidly buy or sell a sizable volume of securities at a low cost and with a limited price impact (IMF 2015). "Market liquidity premium" is defined as the price impact of a given trade on the market (Baranova and others 2017).

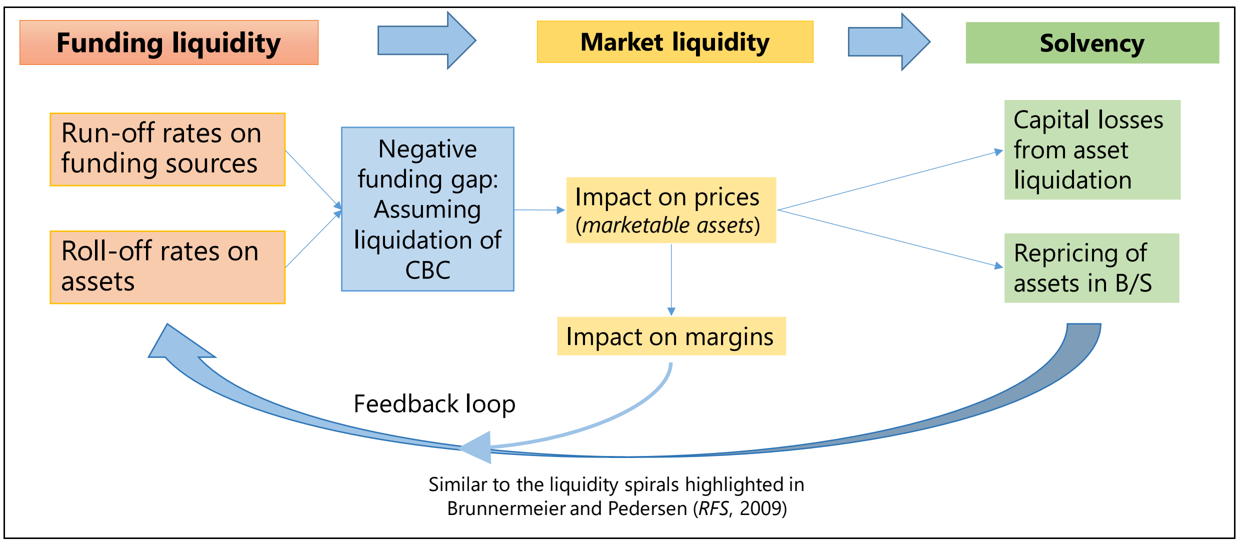
their papers was difficult due to the paucity of empirical analyses that reveal the price impact for a given volume of assets sold in fire sales.

III. The Framework

A. Overview

A key element of our framework is the methodology to estimate the impact of asset liquidation on asset prices (that is, haircut ratios) in stress scenarios. The estimation of asset haircuts during systemic liquidity events raises a practical question in stress tests: how much below current market prices? In the Markov regime-switching models, we assume that market liquidity would switch from a high-liquidity regime to a low-liquidity regime during systemic liquidity events, increasing the market liquidity premia and reducing asset prices. Our framework (for the purpose of stress testing) can be summarized by the following loop with three steps (Figure 2):

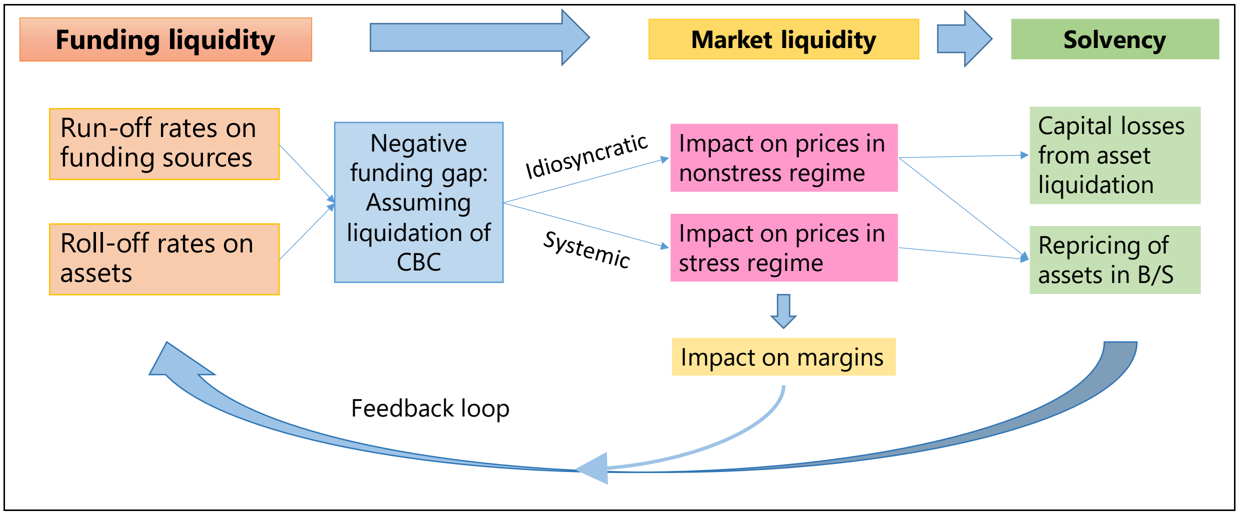
Figure 2. Transmission of Shocks and Solvency-Liquidity Feedback Loop



While a solvency crisis may happen before a liquidity crisis, we focus on the situation when funding liquidity shocks (for example, due to unforeseen wholesale or retail funding withdrawals) lead to a shortage of liquid assets in a group of banks. Funding liquidity challenges develop into market liquidity problems when one or multiple banks try to liquidate similar assets. In the next stage, market liquidity problems lead to further impact on stock of fair value securities (which are marked-to-market). This leads to further losses, which have an impact on a solvency position of a bank(s), and may lead to further withdrawals (funding liquidity problems).

Solvency-liquidity shock transmission mechanisms have different impacts in non-stress and stress regimes, with haircuts being higher in the latter. By systemic stress regime, we assume a situation where multiple institutions are affected and face liquidity shortages; in this case, haircuts are driven by a stressed (low-liquidity) regime. When there is no stress in the markets, and only one or a few institutions face liquidity issues, impacts on prices of assets they liquidate are driven by a non-stress regime haircuts (Figure 3). As an indicator for when markets are in stress and when not (regime switching), we use market volatility indexes.

Figure 3. Transmission of Shocks in Stress and Non-Stress Regimes



A fire sale of assets in our framework happens when funding shocks (for example, due to wholesale funding withdrawal) lead to the need for the sale of assets by financial institutions and is coupled with overall risk aversion of multiple market participants (buyers), which offer lower quotes or are hesitant to buy multiple assets at all. A fire sale is a forced sale of an asset at a price substantially below the fair, fundamental price of that asset (or so-called "intrinsic value," that is, the sum of discounted future cash flows generated by that asset). In this regard, a fire sale has two components: (1) a forced sale (that is, fire sales would not happen without liquidity problems); and (2) a transaction price below the fundamental value (that is, there is an arbitrage opportunity for the buyer). These two features separate fire sale phenomena from burst-of-asset price bubbles. Fire sales of assets depend on both sides of the equation: demand and supply. When a financial institution that faces liquidity constraints (seller) needs to liquidate assets at low prices below fundamental ones, the buyer receives not only risk premium, but also higher illiquidity premium for the asset it buys in the market.

We describe the following steps of modeling solvency-liquidity interactions below.

B. Funding Liquidity: Shocks, Liquidity Needs, and Aggregation of Asset Liquidation

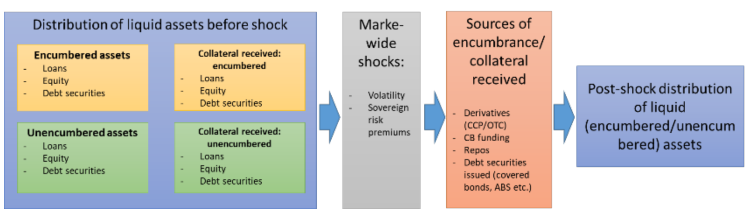
Funding liquidity risk has evolved over time and takes many forms, from deposit outflows to more complex funding arrangements. These include undrawn loan commitments, obligations to repurchase securitized assets, margin calls in the derivatives markets due to a move toward Central Clearing Counterparties (CCP; Box 1), and wholesale short-term loans.

Box 1. Contingent Liquidity

While collateralized lending plays a vital role in mitigating risks in a network of financial institutions, it may be an additional potential source of fire sales because of contingent liquidity risks. Such contingent risks arise because of: (1) repos (securities financing transactions); (2) derivatives; and (3) rehypothecation. These contingent financial instruments require parties to exchange initial and variation margins, which might be the cause of fire sales of assets were the counterparty short of decent quality collateral (cash and/or government bonds). As noted by Geanakoplos (2010), haircuts to derivatives and securities lending transactions may be determined endogenously and lead to negative feedback loops.

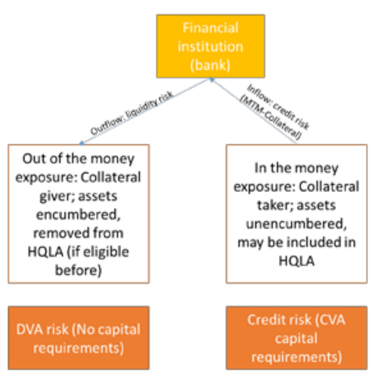
Contingent liquidity risks arise from financial contracts, such as repos (or securities financing transactions [SFT] in broader terms) and derivatives. Compared to behavioral liquidity flows, contingent ones are contractual, however contingent on market events, such as change in value of securities or a derivative being in or out of money. The importance of contingent liquidity risks increased due to migration of OTC SFTs and derivatives into centralized clearinghouses as well as bilateral contract margining requirements. Figure 1 below provides a high-level overview of how contingent liquidity risks arise and how they impact the liquidity position of a bank. In a nutshell, a market-wide shock could lead to a decline in the value of collateral that a bank posted on its own behalf. At the same time, a bank may also receive collateral on the opposite transaction, such as a reverse repo. Collateral is typically placed and received in high liquid assets, such as cash or sovereign bonds (although there are instances when collateral is posted in less liquid assets, such as equities).

Figure 1. Contingent Liquidity Risk Overview



The net effect is the most important in mitigating contingent liquidity risks, that is, if a bank has balanced its own trading position and has no large unidirectional bets in the market, it would post and receive collateral, thus liquidity needs would be netted, especially if contracts were cleared via CCPs (Figure 2).

Figure 2. The Role of CCPs in Liquidity Management



If a bank needs to post more collateral than it receives, its asset encumbrance (AE) ratio goes up, which dries out CBC and may lead to further idiosyncratic shocks, such as the inability to rollover unsecured wholesale funding. Unless the stress tester has very granular data, it would be hard to estimate the effect of additional liquidity needs (albeit a rough approximation may be obtained by repricing all repos and reverse repos across all maturity horizons).

To estimate the impact from funding liquidity shocks under stressed conditions, a stress tester needs to use data about asset structure, and contractual and behavioral cash flows of a bank as well as the banking system as a whole. These data are typically obtained from supervisory returns.

The sequence of funding liquidity analysis is based on the following steps: (1) identification of reasons for asset liquidation; (2) liquidity gap (based on maturity gap analysis using contractual and behavioral cash flows) for each bank; and (3) liquidity risk management and optimization strategy of each bank in the system.

Under negative funding liquidity shocks, a bank might be unable to roll over short-term (or maturing) funding and forced to liquidate assets to cover the liquidity shortfall. In our analysis, we focus on this reason[8].

Liquidity gaps can be calculated using contractual and stressed cash flows over respective time buckets. Under extreme stress situations, behavioral cash flows would approach contractual ones, as customers would be hesitant to extend funding (this is especially important in case of wholesale funding). A liquidity gap in each time horizon would be closed using available liquidity buffers or assets included in the CBC.

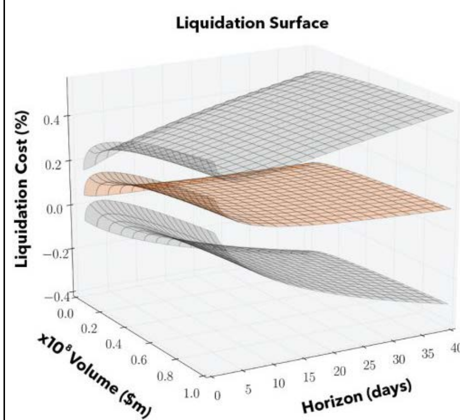
Banks' optimization strategies typically vary. To minimize the risk of asset revaluation, a bank may consider selling the asset over longer time horizons (depending on contractual and behavioral liquidity gaps, for example, when withdrawals may happen)[9]. This strategy would minimize impact on market prices as shown in an example by Casey and others (2017) (Figure 4).

[8] There are three potential reasons for asset liquidation. The first one is motivated by profitability risk. A bank might try to liquidate assets that become "unprofitable" (for example, low-yielding assets funded via short-term wholesale funding). Liquidation leads to the shift in asset composition, for example, toward riskier loans. The selloff of unprofitable assets might have systemic effects (that is, induce fire sales) if multiple banks follow the same strategy. The second reason is due to regulatory constraints. For example, a bank may be forced to reduce its risk-weighted assets or increase holdings of high-quality liquid assets due to capital or liquidity regulations. Such motivation could lead to changes in the composition of the balance sheet. The third reason is funding liquidity risk itself.

[9] In case of long-term profitability risk as well as change in regulatory requirements, outright sales would be the solution; in this case, however, a bank may need to consider the effects of fire sales on immediate mark-to-market valuations.

In case of liquidity shocks, banks have several behavioral options to avoid costly fire sales. For example, banks can use secured funding transactions (for example, repos, collateral swaps) including transactions with central banks (for example, drawing on lending facilities). In this case, banks would minimize or avoid the impact of asset sales on market prices by pledging securities in the market or central bank against cash. Such transactions are possible up to the full amount of assets available for encumbrance minus haircuts[10]. Therefore, asset fire sales would be the strategy of last resort. At the same time, repos are subject to margin calls, thus could elevate liquidity risks during stress times. For example, funding liquidity may suddenly vanish for a given financial institution when it faces reputational or legal issues and raises related concerns from its counterparties. For example, the Lehman Brothers bank in the US had collaterals; however, triparty repo counterparties were concerned about the bank's solvency and were reluctant to enter or extend repos with it (see Copeland and others 2014). Box 1 illustrates how contingent liquidity risks arise and are linked with AE.

Figure 4. Sales Amounts, Haircuts, and Liquidation Horizon



Surfaces showing Upper (75%), Middle (50%), and Lower (25%) confidence bands. Source: Casey and others (2017).

Based on the supervisory data of cash flows and AE, a stress tester needs to consider banks' ability to obtain liquidity using repos with central banks as a substitute for market-based repo or outright asset sales. We only consider outright sales (asset liquidation) in our model; although the stress tester may wish to model haircuts (or funding cost shocks) for secured funding transactions (see Appendix II for a discussion about potential extensions).

The pecking order of liquidation matters in theory, but banks may have limited options in reality given the externality from fire sales[11]. For example, in case of a prolonged systemic crisis where many banks are experiencing liquidity shortages, these banks may be willing to hoard liquidity and try to liquidate less liquid assets first. However, they may find themselves only able to sell liquid assets due to larger haircuts on less liquid assets and a lack of demand. In case of an idiosyncratic shock to a bank, the bank may be able to liquidate less liquid assets. However, liquidation of such assets may also signal to the markets that the bank has

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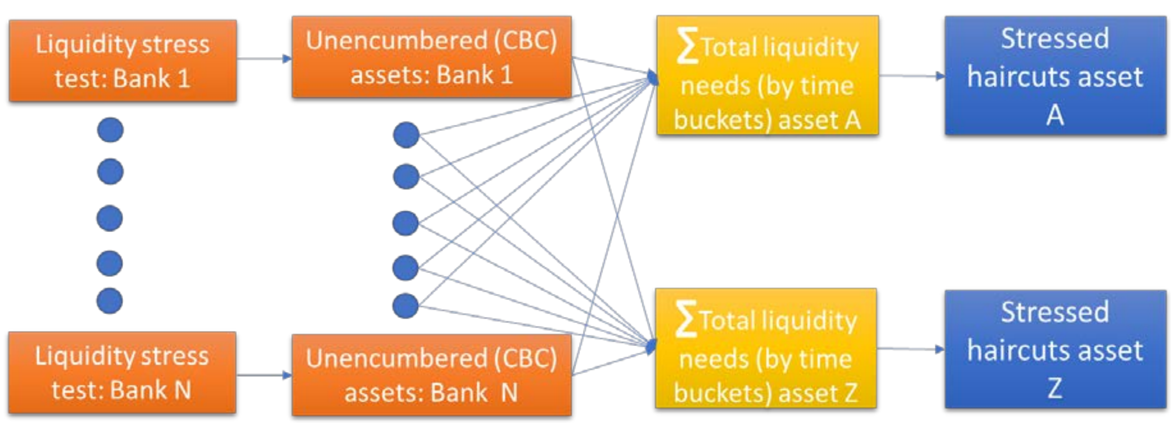
[10] Market haircuts for repo transactions are typically available from multiple information sources, such as London Clearing House, and Bloomberg, etcetera. Haircuts are based on the duration of the repo as well as the quality of securities pledged. Changes in the market prices of securities pledged lead to daily margin calls.

[11] We do not model the pecking order explicitly; however, our tool allows for simple assumptions about the asset liquidation strategy of each individual bank.

liquidity problems and stimulate further liquidity outflows. Hence, the bank may be unwilling to liquidate illiquid assets first. The pecking order also depends on the information and assumptions that markets have about the liquid (and unencumbered) assets of other banks. Banks have typically incomplete information about which and how many securities other banks hold, and do not know other banks' funding shortages. Therefore, each bank may fear that it may be worse off if it sells only liquid securities while other banks start selling less liquid securities, which may lead to significant price changes and marked-to-market losses. In this case, the opposite may happen: each bank may choose to sell less liquid securities first to minimize the impact on market prices before it is affected by the fire sales by other banks.

Identification of systemic and idiosyncratic events matters for the size of the haircuts. Multiple banks face liquidity shortages in case of systemic liquidity events. Haircuts would be larger, as they depend on how much of the aggregate assets may be liquidated by type and currency of assets, assuming that higher outflows require financial institutions to balance these with inflows from asset liquidation (Figure 5). Since this aggregation is purely on the supply or sales side, the stress tester could also check whether the change in the landscape of dealer intermediation has affected the private sector capacity to absorb such liquidation (for example, by looking into the balance sheets of pension, insurance companies, or other financial intermediaries)[12].

Figure 5. Aggregation of Liquidity Needs for Haircut Calculation



Source: Authors.
This chart ignores the fact that additional feedback loop may exist due to contingent liquidity risks, i.e., stemming from margin calls on encumbered assets. See Box 1 above.

C. Market Liquidity: Haircut Estimation

We only consider marketable assets or securities in the modeling of the haircuts for asset fire sales. This is because non-marketable assets by definition do not typically have a market to

[12] In many cases, however, it is difficult to conduct such a demand-side analysis due to the lack of data.

trade. Therefore, it is difficult to measure market liquidity—the ability to rapidly buy or sell a sizable volume of securities at a low cost and with a limited price impact—for these assets.

Since market liquidity is prone to suddenly drying up, large system-wide fire sales of assets are likely to be associated with lower market liquidity, potentially triggering a regime shift in the level of market liquidity. Following IMF (2015) and Flood and others (2015), we define the aggregate market liquidity of an asset class as a measure of market liquidity averaged across all securities in the asset class, and assume that the aggregate market liqudity has a regime-switching behavior—or in other words, it could switch abruptly between different regimes (for example, a high-liquidity regime and a low-liquidity regime). The switch from one regime to another could be triggered by asset fire sales by some banks in order to cover their negative funding gaps due to funding liquidity constraints. This may lead to significant valuation losses through both implementation shortfall and repricing of marked-to-market assets. The latter channel affects not only the banks that conduct fire sales but also the other banks in the system that also hold these assets.

Markov regime-switching models have been used in literature to study the likelihood that aggregate market liquidity suddenly evaporates, that is, switches from a high-liquidity (or non-stress) regime to a low-liquidity (or stress) regime. As shown by IMF (2015), the probability of being in a low-liquidity regime could be affected by both structural and cyclical factors such as regulatory changes and market volatility. For example, market liquidity can quickly disappear when volatility increases or funding conditions deteriorate.

We assume that the regime-switching behavior of aggregate market liquidity is linked to the nature of the funding shortfalls. More specifically, we assume that market liquidity would switch to a stress regime (that is, a low-liquidity regime) under the asset fire sales in systemic events, implying a higher price impact, but would remain in the nonstress regime (that is, a high-liquidity regime) under asset fire sales in idiosyncratic events. This is a simplifying assumption (Table 1)[13]. Under this assumption, the resulting lower asset prices in both systemic and idiosyncratic events affect asset valuations and margin requirements for all banks in the system. But such an impact on prices could be significantly larger in systemic events than in idiosyncratic events due to a higher market liquidity premium in the former. Therefore, although the stress regime may overestimate the price impact, it is of particular interest in the context of stress testing.

[13] For example, during systemic events when multiple financial institutions face liquidity shortfalls, market liquidity of the assets that are sold may not fall sharply if fundamentals of such assets or financial institutions are strong.

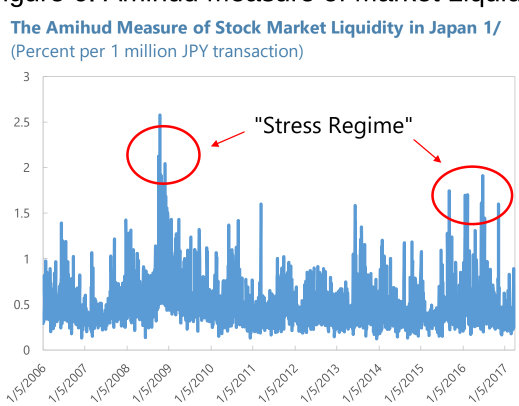
Table 1. Classification of Liquidity Events

	Stress regime	Non-stress regime
Systemic	Occurs when multiple financial institutions face liquidity shortfalls and when market liquidity shock is due to investors' loss aversion and/or increase in volatility.	Occurs when multiple financial institutions face liquidity shortfalls, but market fundamentals are sound (i.e., no change in volatility and/or levels of risk tolerance).
Idiosyncratic	Occurs when one or a few small banks or other financial institutions face liquidity shortfalls and when market liquidity shock is due to investors' loss aversion and/or increase in volatility.	Occurs when one or a few small banks or other financial institutions face liquidity shortfalls but market liquidity conditions are not affected.

Source: Authors.

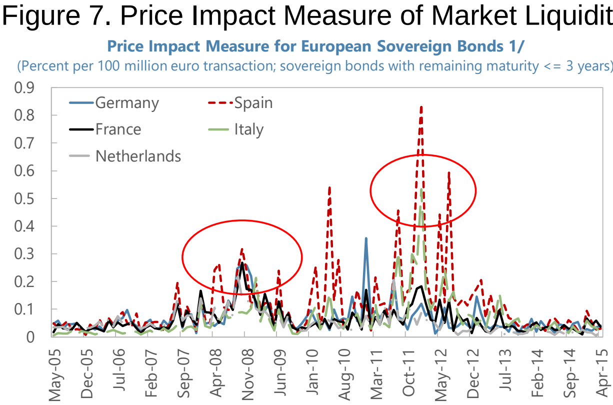
Security-level measures of market liquidity are aggregated for a certain asset class to obtain measures of aggregate market liquidity. Different measures of market liquidity at the security level have been developed in literature. Two widely used market liquidity measures of price impact in literature (see, for example, IMF 2015) are: (1) the Amihud (2002) measure—defined as the ratio between the absolute value of daily returns and daily trading volume of a frequently traded security; and (2) the price impact measure—defined as the slope coefficient of a regression of price change on signed order flow (buyer-initiated trades minus seller-initiated trades). The price impact measure assigns "signs" to trades, making it more suitable for modeling the haircuts for asset fire sales, as most fire sales are seller- rather than buyer-initiated trades. As shown by the 2017 Japan FSAP (IMF 2017), the Amihud measure of the Japanese stock market varies over time and exhibits regime-switching (Figure 6). Similarly, IMF (2015) shows that the price impact measure for European sovereign bonds increased rapidly during the global financial crisis and European debt crisis (Figure 7).

Figure 6. Amihud Measure of Market Liquidity



Sources: Bloomberg, L.P.; and IMF staff calculations.
1/ Amihud measure is calculated for each stock in Nikkei 225 as the absolute daily return divided by daily trading volume. The measure presented here is the median across all the stocks in Nikkei 225.

Figure 7. Price Impact Measure of Market Liquidity



Sources: MTS and IMF staff estimates.
1/ Price impact measure is defined as the slope coefficient of a regression of price change on signed order flow (buyer-initiated trades minus seller-initiated trades).

The aggregate market liquidity measures tend to be correlated across asset classes and countries. For example, if we define asset class of sovereign bonds by residual maturity and country, then we would expect short-term German bonds to be correlated with medium-term German bonds and short-term French bonds. Therefore, these asset classes may share the same (that is, stress or nonstress) regimes, as well as exibit the so-called flight to quality effect. As a result, in addition to the estimated regimes for each asset class individually, we also estimate "common" regimes, assuming that certain asset classes share the same stress or nonstress regimes.

We use the following steps to estimate a simple regime-switching model for the aggregate market liquidity measure of each asset class:

- Step 1: Identify the marketable asset classes and securities that banks hold as CBC and calculate the price impact measure at the security level using transaction data[14];
- Step 2: Average the security-level price impact measures for all securities in the same asset class to obtain aggregate price impact measure for each asset class; and
- Step 3: For each asset class j, estimate the following baseline Markov regime-switching model[15]:

$$PI_t^j = \beta_0^{j,s} + \varepsilon_t^{j,s}, \tag{1}$$

where PI_t^j is the aggregate price impact measure averaged across all securities in the asset class j, and s denotes the regime of the aggregate price impact measure. For simplicity, two regimes are assumed, notably, a non-stress (or high-liquidity) regime and a stress (or low-liquidity) regime, but one could also choose a different number of regimes based on the estimation results. $\beta_0^{j,s}$ is the constant of interest that varies across regimes and $\varepsilon_t^{j,s}$ is the error term with mean zero and variance σ_s^2. The variance σ_s^2 is also assumed to vary across the two regimes[16].

The impact of asset sales on the prices depends on the price impact measure of that asset class and the total amount of securities offered to sell in that asset class. To determine the amount of sales for each asset class, one would need to use information or make assumptions about the pecking order of sales. The amount of securities a bank needs to liquidate to offset the negative funding gap is available from a liquidity stress test. In other words, one would need the information on how much securities in each asset class will be sold in which order and time horizon for each bank. Since the focus of the paper is to estimate the haircuts, we do not attempt to model the pecking order and time horizon of sales, and simply assume that

[14] The price impact measure is calculated daily in this paper.

[15] The specification is similar to Flood and others (2015).

[16] We also consider the case where the variance of the error term is the same across regimes.

bank i needs to liquidate Vol_i^j amount of securities that belong to asset class j. Therefore, the total amount of securities in asset class j that will be liquidated by all banks, Vol_{all}^j, can be expressed as

$$Vol_{all}^j \equiv \sum_{i=1}^{I} Vol_i^j \tag{2}$$

where I is the total number of banks in the system[17].

Based on the baseline Markov regime-switching model, we calculate the price impact for each asset class using the total amount of fire sales. More specifically, since the price impact measure indicates the impact of a one-unit (net) trade on the price, we can assume a linear relationship[18] with a scenario conditional floor between the price impact of fire sales and the total amount of fire sales.[19] The price impact for each asset class j in regime s can be calculated as $\beta_0^{j,s} \cdot Vol_{all}^j$.[20] Since we assume that market liquidity of an asset class remains in the non-stress regime in idiosyncratic fire-sale events, then the price impact for asset class j in idiosyncratic events could be calculated as:

$$\beta_0^{j,non-stress} \cdot Vol_{all}^{j,non-stress} \tag{3}$$

where $Vol_{all}^{j,non-stress}$ represents the total amount of securities in asset class j that are liquidated by all banks in the nonstress regime. Similarly, since we assume that market liquidity of an asset class switches from the nonstress regime to the stress regime when banks start to liquidate this asset class, the price impact should be calculated as:

$$\beta_0^{j,stress} * Vol_{all}^{j,stress} \tag{4}$$

[17] Given that the time period of liquidation could be longer than one day (for example, weeks), one could assume different scenarios of liquidation strategies. In this context, the total amount of liquidation on a particular day would depend on the specific liquidation strategy.

[18] The floor is important, as without the model, which estimates the demand of securities, it would be possible to have haircuts that would exceed realistic values (that is, they may even become negative). Assumed floors depend on types of securities and can be very high for sovereign bonds and low for illiquid, opaque securities.

[19] This is a simplifying assumption, as the actual price impact of a trade could be a non-linear function of the size of the trade. Moreover, a linear relationship implies that a sufficiently large trade could lead to a price decline of over 100 percent, which would never happen in reality. Having said that, since the price impact measure quantifies the “average” impact of a one-unit trade on prices, one may make the simplified assumption when the size of the trade is not “too” large to reduce post-trade prices to negative values. IMF (2015) uses the same linearity assumption in calculating the price impact measure.

[20] As explained above, the total amount of fire sales is obtained from the liquidity stress test, and a pecking order of fire sales of different asset classes needs to be assumed before applying the methodology.

where $Vol_{all}^{j,stress}$ denotes the total liquidation amount by all banks in the stress regime. As shown in the practical example below (see Section IV), the price impact can be much larger in the stress regime than in the nonstress regime, depending on the total fire sale amount and the specific asset class[21].

Since aggregate market liquidity could be affected by market uncertainty (see, for example, IMF 2015), we also run the Markov regime-switching model (1) with a measure of market uncertainty. A commonly used measure of market volatility for the United States is the Chicago Board Options Exchange (CBOE) VIX index. Since the price impact of an asset class could be more affected by the market volatility of its own jurisdiction than that of the US, we choose the volatility index according to the jurisdiction of the asset class. Although the volatility indexes in major advanced economies tend to comove with the US VIX, the dynamics show some key differences during certain episodes (Figure 8). For example, during the peak of the Europen debt crisis in 2012, the volatility indexes of Italy and Spain experienced much larger increases than the US VIX. Therefore, to capture the effects of both the US VIX and country-specific factors on market volatility, we first decompose the country-specific volatility index into a common term that can be explained by the US VIX and a residual term that is orthogonal to the US VIX. More specifically, if asset class j belongs to country c, we run the following simple regression:

$$V_t^c = \alpha_0 + \alpha_1 \cdot VIX_t^{US} + \epsilon_t^c \tag{5}$$

to decompose the volatility index of country c into a constant, a common term ($\widehat{\alpha_1} \cdot VIX_t^{US}$), and a country-specific residual term ($\widehat{\epsilon_t}$). Here, $\widehat{\alpha_1}$ is the estimated coefficient α_1 and $\widehat{\epsilon_t}$ is the residual of the regression. This decomposition allows us to design a scenario of the country-specific volatility index by changing the residual $\widehat{\epsilon_t}$ if a scenario of the US VIX is available. With this decomposition, we estimate the following Markov regime-switching model for asset class j:

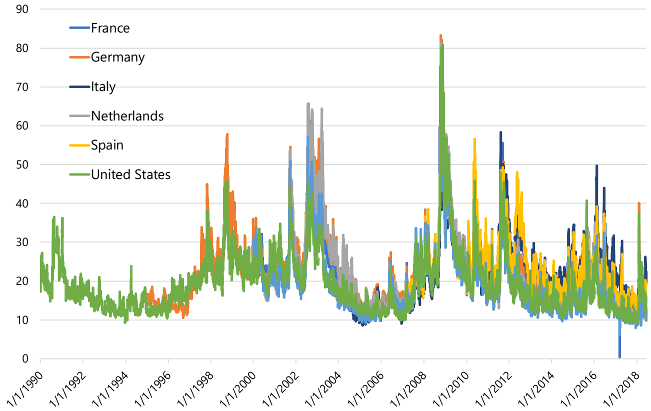
$$PI_t^j = \beta_0^{j,s} + \beta_1^{j,s} \cdot VIX_t^{US} + \beta_2^{j,s} \cdot \widehat{\epsilon}_t + \varepsilon_t^{j,s}. \tag{6}$$

In this specification, the effects of the US VIX and the residual term, $\widehat{\epsilon_t}$, on the price impact measure of asset class j vary across the nonstress and stress regimes[22].

[21] It is worth noting here that aggregating security-level price impact measures to the asset class level is to simplify the calculation, and the calculation could also be conducted at the security level if more granular data of each bank's CBC are available.

[22] Lagged VIX and residuals could also be used to mitigate the endogeneity problem. However, the results in the case study in the next section do not change when lagged VIX and residuals are used—likely due to the high autocorrelation of VIX. Moreover, we do not assume that the regime-switching probabilities (e.g., the probability of switching from the non-stress regime to the stress regime) depend on the VIX variables. This is because modeling such probabilities as a function of the VIX variables would significantly increase the computational burden and the instability of estimates.

Figure 8. Volatility Indexes for Selected Countries



Sources: Bloomberg, L.P.; and Haver Analytics.
1/ CAC 40 volatility index for France, VDAX-New index for Germany, call-implied volatility index PSI 20 for Italy, AEX volatility index for Netherlands, IBEX 35 volatility index for Spain, FTSE 100 volatility index for United Kingdom, and the CBOE market voatlity index for United States.

The model estimates depend on (1) whether regimes are different or common across asset classes; (2) whether the variance of the error term is regime-switching or not; and (3) whether the model includes a volatility index or not. Based on the different combinations, we compute the haircuts of fire sales based on the following five specifications, each of which has two regimes (non-stress and stress):

1. Asset class-specific regimes and regime-switching variances without a volatility index (as in equation 1);

2. Asset class-specific regimes and non-regime-switching variances without a volatility index (as in equation 1);

3. Common regimes and regime-switching variances without a volatility index (as in equation 1);

4. Asset class-specific regimes and regime-switching variances with a volatility index (as in equation 6);

5. Asset class-specific regimes and non-regime-switching variances with a volatility index (as in equation 6).

Specification 1 is the baseline specification to estimate asset class-specific regimes, and the other specifications with asset class-specific regimes are mainly for robustness checks. Equation (6), with common regimes, is not considered a separate specification in this paper due to the significantly increased computational burden after including the volatility variables in the Markov regime-switching model. For our analysis, we built a Matlab program and an accompanying Excel-based tool (see Appendix III). The Matlab program is used to estimate the Markov regime-switching models presented above, and the Excel-based tool is used to estimate the haircuts based on the total amount of assets sold by all banks in the system.

D. Solvency: Asset Valuation and Losses

Estimated values of haircuts provide us with estimates of feedback loops for further use in solvency tools. Liquidity shocks lead to liquidation of assets, accounting losses, lower capital, and subsequantly higher funding costs and further deterioration of funding liquidity. In the next round, changes in capital adequacy and leverage ratios also typically lead to further changes in funding costs (that is, a lower capital adequacy ratio (CAR) leads to higher funding costs and vice versa) and more severe funding liquidity problems[23]. In other words, with the changes in solvency risks, we return to step 1 and continue with the loop until the change in the CAR becomes very small.

Banks face two types of losses from fire sales: implentation shortfall and marked-to-market losses. The implentation shortfall, as it is called in the literature on optimal trade execution (for example, Almgren and Chriss 2000), refers to the difference between the market price at the time of sale and the volume-weighted average price (VWAP) during liquidation. This VWAP lies somewhere between the pre- and post-fire-sales prices. In the empirical examples below, we will use 1/2, which corresponds to a VWAP midway between the pre- and post-fire-sales prices, following Cont and Schaanning (2017). Therefore, bank i's losses in regime s (nonstress or stress) can be written as:

$$Losses_i^s = \sum_{j=1}^{J} \left[\left(\frac{1}{2} * \beta^{j,s} * Vol_{all}^j \right) * Vol_i^j + \left(\beta^{j,s} * Vol_{all}^j \right) * Stock_i^j \right] \quad (7)$$

where J denotes the total number of asset classes, $\beta^{j,s}$ is the price impact of asset class j in regime s, and $Stock_i^j$ is bank i's total holdings of securities that belong to asset class j. In particular, $\beta^{j,s}$ is a regime-switching constant in model (1) but a regime-switching function of VIX variables in model (6).

The framework was applied to banks, but it can be extended to estimate price impact measures as well as haircuts from asset sales of multiple participants, including asset managers (mutual funds) and insurance and pension fund companies. The latter (compared to banks) may be more active in long-term bond markets. Moreover, the framework can be incorporated into FSAPs, as it is based on standard stress-testing tools, data, and software. In the next section, we offer an application of our model to estimate haircuts in both stress and nonstress regimes for selected European sovereign bonds held by large banks in the euro area and subsequently impact banks' capital levels.

[23] See Appendix II for further details on calibration of funding cost loop.

IV. Example: The Case of Euro Area Banks

A. Data

We estimated potential fire-sale losses for the 29 largest euro area banks using data from the 2016 European Banking Agency (EBA) transparency exercise. The data contained banks' sovereign exposures by country and remaining maturity. In addition to this, we used data about regulatory capital and risk-weighted assets (RWA).

We grouped banks according to their business models into three categories: G-SIBs (as in the Financial Stability Board's (FSB) list, that is, internationally well-diversified banks with diverse sources of income and diversified asset holdings); internationally active banks (less diversified compared to G-SIBs and more focused on domestic activities, not on the FSB list); and banks with purely domestic focus (serving domestic markets).

Transaction-level data on prices and trading volumes for European sovereign bonds are needed to calculate the bond-level price impact measure. Such data were obtained from the dataset used in IMF (2015), which was obtained from the company MTS Markets (MTS), containing the top of the order book for all European sovereign bonds traded on the MTS platform from May 2005 to April 2015. The price impact measure is calculated on a daily basis and at the bond level using the detailed price and trade information. For simplicity, we aggregate the bond-level price impact measure into 20 asset classes according to the residual maturity and issuer country of the bonds, namely, sovereign bonds issued by France, Germany, Italy, Netherlands, and Spain, with a residual maturity of one to three years, four to six years, seven to 11 years, and 11+ years[24]. Although we only consider four maturity buckets in this exercise, having more maturity buckets does not alter the results qualitatively.

Most of the banks' sample sovereign bond exposures are concentrated into six countries: France, Germany, Italy, Netherlands, Spain, and United States (67 percent), with the majority of them designated as traded assets, thus subject to marked-to-market repricing[25] (Figures 9 and 10).

[24] One caveat is that the sales of sovereign bonds could also affect the prices of other securities. However, we can only focus on the sales of sovereign bonds in this paper given the absence of public data on banks' holdings of other securities. Having said that, the same Markov regime-switching approach could be applied to other types of securities for the purpose of stress tests.

[25] The data we used are from 2016, hence assets were classified as Held for Trade (HFT) and Available for Sale (AFS). IFRS9 classification which is applied since January 2018 eliminated AFS and HFT classification; at the same time, majority of debt securities still fall under market price valuation for accounting purposes (Fair Value). From an economic perspective, internal classification does not influence price under fire sales of these assets (for example, losses due to implementation shortfall as in our example) but would affect the second component of price impact – marketable securities held for trading purposes (i.e. Fair Value under Profit and Loss). Banks which reclassified debt securities as Fair Value through Other Comprehensive Income (FVOCI) would need to estimate the direct market price impact on securities remaining in their balance sheets as well as new provisioning requirements.

Figure 9. Sovereign Bond Holdings

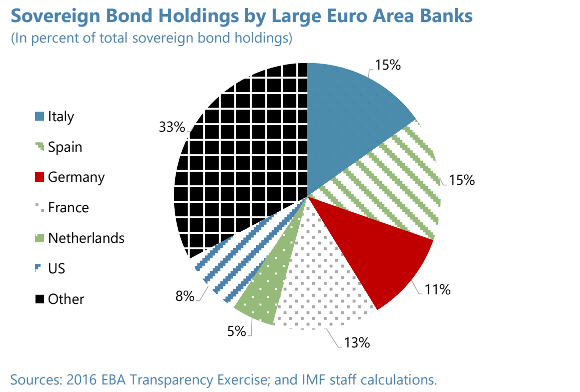
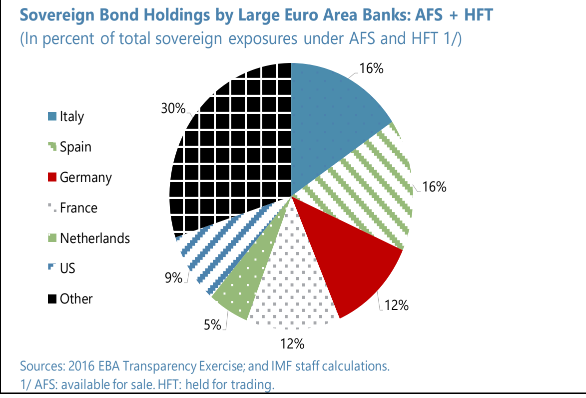


Figure 10. Accounting Classification of Sovereign Bond Holdings



Based on exposure data, we focus on the largest five sovereign exposures within the euro area: France, Germany, Italy, Netherlands, and Spain[26]. The remaining bond maturity is also important: price impacts tend to be larger for long-term bonds as these tend to be less liquid. The majority of banks' holdings of sovereign debt securities fall under the first zero to three years category, with negligible holdings of long-term securities seven to 11 and 11+ years. For estimation purposes, we grouped remaining maturities of securities into four buckets: zero to three years, four to six years, seven to 11 years, and 11+ years. A more detailed analysis would require a more granular grouping (for example, by International Security Identification Number (ISIN) or Committee on Uniform Security Identification Procedures (CUSIP) number to estimate liquidity of each individual bond issuance), but this also requires using data that contain ISIN/CUSIP identifiers of securities in banks' balance sheets.

B. Simulations

The simulation exercise focuses on the following five specifications[27]:

1. Country/maturity-specific regimes and regime-switching variances without a volatility index (as in equation 1);

2. Country/maturity-specific regimes and non-regime-switching variances without a volatility index (as in equation 1);

3. Common regimes across all countries in the same maturity bucket and regime-switching variances without a volatility index (as in equation 1);

[26] Securities level trading data for U.S. sovereign debt securities was not available to us at the time of analysis.

[27] Hereafter, we denote the regime for each combination of country and maturity bucket by country/maturity-specific regime.

4. Country/maturity-specific regimes and regime-switching variances with a volatility index (as in equation 6); and

5. Country/maturity-specific regimes and non-regime-switching variances with volatility index (as in equation 6).

For simplicity, we assume that there is no pecking order in fire sales and the time of liquidation is one day. In other words, all banks sell the same share of their sovereign bond holdings in one day. We assume that to offset the negative funding gaps from the liquidity stress test, all banks need to sell 5 percent of their sovereign bond holdings of the largest five sovereign exposures in their CBC.

For specifications 4 and 5, with volatility variables, we assume that US VIX increases to 23.9 percent as in the recent US Fed scenario for stress testing. We also assume that the respective market volatility indexes for the five countries increase by two standard deviations from their values observed at the end of Q1 2018.

Following Cont and Schaanning (2017), we assume that the implementation shortfall is 50 percent.

The exact strategy banks would employ to minimize price impact and maximize proceeds from asset sales is highly uncertain, as it employs multiple parameters, such as amounts of securities offered by each type of security in a pool of unencumbered liquid assets, including assumptions about time required to sell these securities. Amounts of securities offered for sale in the market at any given point in time during periods of liquidity stress is a function of banks' ability to obtain liquidity via repos with central banks and private market counterparties, and their ability to swap less liquid assets to liquid ones to meet immediate liquidity pressure or regulatory requirements at the end of the reporting period. The precise estimation and optimal sales strategy is beyond the scope of this paper; at the same time, central banks or supervisors may use supervisory data to derive a loss minimizing strategy for every bank (if supervisory data contain information about the amount and type of securities held by each institution and the daily liquidity shortage) given the view "from the top" about collective liquidity needs.

The accompanying Excel file (see description in Appendix III) allows a stress tester to enter granular assumptions about sales of each security (by type and maturity) for each bank.

C. Haircuts

The estimated haircuts are calculated based on fire sales of 5 percent of bond holdings[28]. The results for the five specifications of our interest are presented in Figure 11[29]. The haircuts of Italian and Spanish sovereign bonds are typically higher than those of Dutch, French, and German sovereign bonds, particularly in stress regimes. This finding reflects differences in the estimated price impact as well as banks' different holdings of sovereign bonds. For example, haircuts on German bonds are calculated according to equations (3) and (4) and hence could be higher than those on Italian or Spanish bonds despite lower price impact for German bonds, if banks are assumed to sell many more German bonds than Italian or Spanish bonds (because they hold a higher amount of German bonds). In other words, the volume effect may prevail, as many banks hold a larger amount of these "safe" bonds. By assuming that banks sell the same share of each bond (5 percent), we implicitly assume that more "safe" bonds are sold during the fire-sale event. Therefore, the generally higher haircuts on Italian and Spanish bonds are mostly due to higher estimated price impact, even after controlling for higher variances during periods of stress in specification 1.

The results for specification 3 with common regimes seem to suggest some "flight to quality" effects in the stress regime. Specifically, the haircuts of Italian and Spanish sovereign bonds in the stress regime in specification 3 are generally higher than those in the non-stress regime (except zero- to three-year Italian bonds). However, in contrast, the haircuts of Dutch, French, and German Dutch bonds in the stress regime in specification 3 are generally lower than those in the non-stress regime. This could reflect the so-called "flight to quality" effects that investors tend to shift from lower-quality bonds to those with higher quality during periods of stress.

The estimated haircuts are statistically significantly different between stress regimes and non-stress regimes in most specifications. In particular, in all the specifications with country/maturity-specific regimes, haircuts in stress regimes tend to be statistically significantly higher than those in non-stress regimes[30]. Since the amount of bonds sold is assumed to be the same between stress and non-stress regimes, the significantly higher haircuts in stress regimes reflect a significantly higher price impact in stress regimes as the systemic fire-sale events trigger a shift in the market liquidity regime during periods of

[28] Five percent is used for illustrative purposes only. The stress tester would link the amount with liquidity stress-test results of each bank and vary from bank to bank; numbers cannot be reported because of data confidentiality issues.

[29] The Markov regime-switching models (1) and (6) with regime-switching variances are estimated with Matlab (see Appendix IV for the description of the Matlab program used in this paper).

[30] The estimation results suggest that there are two regimes. In other words, the estimated coefficient of interest in one regime is statistically significantly higher than that in the other regime. For example, the estimated 95-percent confidence interval for the haircut ratio of German sovereign bonds with a residual maturity of four to six years in specification 2 is [0.2%, 0.3%] for the non-stress regime, which is well below the 95-percent confidence interval for the stress regime [1.7%, 2.0%].

stress. This difference in the price impact between non-stress and stress regimes could have different effects on banks' capital levels and is particularly important given the purpose of stress tests.

The haircuts in the specifications with non-regime-switching variances (specifications 2 and 5) are typically much higher than those in the specifications with regime-switching variances (specifications 1 and 4), mainly due to higher volatilities in stress regimes. Generally speaking, specifications 1 and 4 seem to be more preferable than specifications 2 and 5 given that the former specifications account for different volatilities between stress and non-stress regimes. In fact, Figure 7 suggests that variances are higher during periods of stress. Moreover, regression statistics also suggest that the specifications with regime-switching variances tend to have better goodness of fit than those with non-regime-switching variances. In this sense, results from specifications 2 and 5 should be treated with caution.

Figure 11. Haircuts on Selected European Sovereign Bonds

(In percent of original prices; assuming selling 5% of bond holdings)

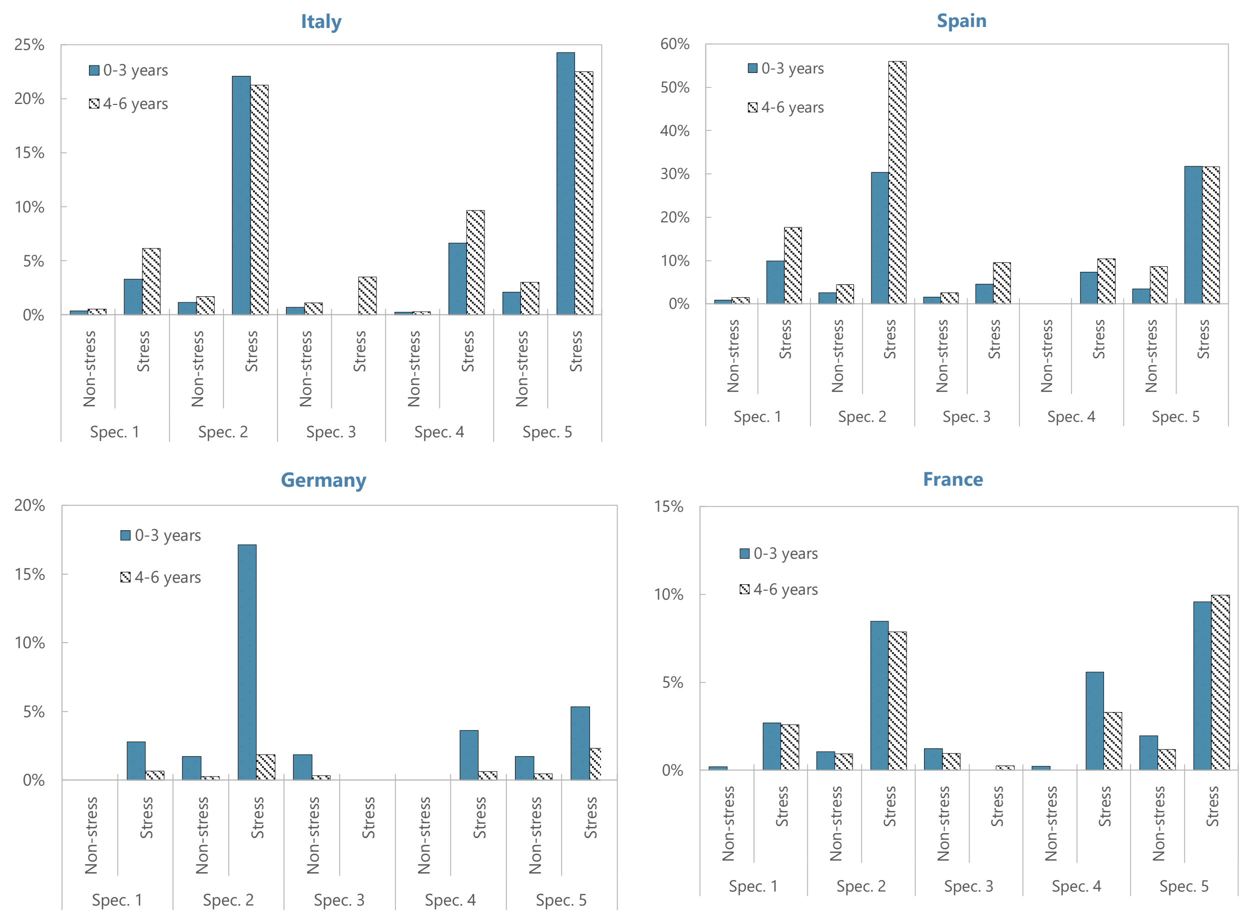
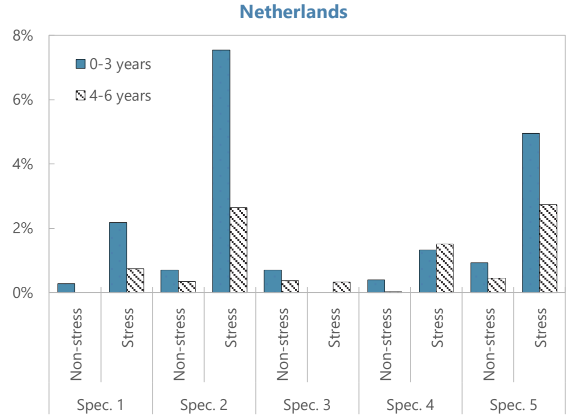


Figure 11. Haircuts on Selected European Sovereign Bonds (continued)

(In percent of original prices; assuming selling 5% of bond holdings)



Sources: MTS; and IMF staff estimates.
Note: Haircuts are based on the total amount sold and thus reflect differences in the price impact as well as differences in holdings of different types of sovereign assets. For example, in case banks sell more German bonds because they hold higher amounts of them, haircuts on German bonds could be higher than those on Italian or Spanish bonds. This would be a hypothetical situation when many institutions want to liquidate German assets at the same time and with large quantities. In practice, the stress tester needs to take into the account scenario, i.e., if German sovereign risk increases, then German bonds would suffer from higher haircuts.

D. Results: Impact on Capital

Applying estimated haircuts on banks' capital is a straightforward exercise. We assume that losses on sales are realized immediately (with a 50 percent implementation shortfall) and fair value of remaining (unsold) assets classified as Available for Sale and Held for Trading (roughly corresponding to IFRS9 classification as Fair Value Other Comprehensive Income and Fair Value Profit and Loss) are affected by a full amount of haircut. We do not reduce RWAs as, based on regulatory treatment, sovereign bonds included in our exercise are treated as zero-risk weighted exposures[31]. Impact on the CAR for each bank *i* and each specification M (as defined in section B) is estimated as follows:

$$CAR_i^{shocked;M} = \frac{CETI\ capital_i - Loss_i^M}{RWA_i} \qquad (8)$$

Where the CET1 is the amount of Core Equity Tier I capital held by bank i; $Loss_i^M$ denotes the losses calculated for bank *i* and specification M as in equation (7).

Assuming all banks sell 5 percent of their sovereign bond holdings in CBC, the impacts of such asset fire sales on banks' capital by model specification and type of bank are presented in Table 2.

[31] Following European law also known as Capital Requirement Regulation (CRR).

Table 2. Results of 5 Percent of Asset Fire Sales

Median CET1 ratios before and after asset liquidation		Bank type		
		G-SIB	Internationally active	Domestic focus
CET1 CAR before asset liquidation		12.72	14.29	14.29
CET1 CAR after asset liquidation	specification 1, stressed	12.29	13.99	13.57
	specification 1, non-stressed	12.69	14.26	14.24
	specification 2, stressed	10.93	13.23	11.50
	specification 2, non-stressed	12.57	14.20	14.06
	specification 3, stressed	12.60	14.18	14.02
	specification 3, non-stressed	12.59	14.22	14.11
	specification 4, stressed	12.22	13.97	13.58
	specification 4, non-stressed	12.70	14.28	14.29
	specification 5, stressed	11.35	13.31	12.20
	specification 5, non-stressed	12.49	14.15	13.96

Source: Authors' calculations.

The results reveal that the impact of direct losses (via asset liquidation) and indirect losses (via asset valuation) on capital is more severe during periods of financial turbulence. A stress tester therefore needs to consider different market liquidity regimes. There is a statistically significant difference between haircuts applied under stress and non-stress regimes. The largest difference is observed in specification 2, where the liquidation of the same amount and composition of assets leads to a 152-bp difference between the impact on banks' CET1 ratio in the stress regime and that in the non-stress regime (weighted average of banks included in the sample), with the stress regime being more severe[32]. The stress tester can also compare the number obtained from the model with asset fire sales to the CET1 number obtained from the solvency stress test without a fire sales loop. Finally, the stress tester can link the CET1 impact with macro variables (for example, credit growth, interest rates, etcetera) and estimate potential second-round effects on real economy. Such simulations go beyond the scope of our paper. Overall, the fire-sales channel in stress tests is an important component that could lead to additional depletion of banks' capital buffers.

Higher losses will also happen in the case of low diversification of assets held for liquidity purposes. For example, banks in our sample, which have a higher share of their own sovereign bonds, are hit more compared to the ones with diversified holdings of liquid assets. This is evident when analyzing business models of banks in our sample. The largest stressed/non-stressed differences are observed in the case of domestic banks. This is not surprising, given their higher share of domestic sovereign bonds (and thus lower asset

[32] The impact in the stress regime is statistically significantly larger than the impact in the non-stress regime. In particular, the 95-percent confidence interval for the impact difference is between 141 bps and 162 bps. This result is mainly driven by the statistically significantly different haircuts between stress and non-stress regimes in the previous section.

diversification effects) in their liquid asset portfolios. Large international banks and G-SIBs in our sample have more diversified portfolios of liquid assets, thus a fire-sale impact on their CET1 capital is lower (including lower differences between stressed and non-stressed regimes). Moreover, an increase in market volatility also leads to higher haircuts and subsequent losses[33]. The heatmap (Figure 12) summarizes our results obtained by running all five specifications. It illustrates one of the key features of liquidity stress tests, namely stress parameter uncertainty. To address the uncertainty, the heatmap can be used to compare haircuts across different market regimes and different assumptions about market volatility.

For example, if a stress-testing scenario includes shocks to market volatility, a system-wide liquidity squeeze, and changes in the central bank collateral framework, stressed haircuts would be more appropriate compared to non-stressed ones. If many institutions fail liquidity stress tests due to negative cash flows (that is, before using CBC to close the cash flow gap), the market regime would also likely to be a stressed one.

Figure 12. Heatmap of Results under Different Models

Bank's CET 1 CAR										
Before asset liquidation	After Asset Liquidation									
	Spec. 1, stressed	Spec. 1, non-stressed	Spec. 2, stressed	Spec. 2, non-stressed	Spec. 3, stressed	Spec. 3, non-stressed	Spec. 4, stressed	Spec. 4, non-stressed	Spec. 5, stressed	Spec. 5, non-stressed
13.19%	13.16%	13.19%	13.05%	13.18%	13.18%	13.18%	13.15%	13.19%	13.11%	13.17%
12.95%	12.71%	12.93%	11.99%	12.87%	12.88%	12.89%	12.68%	12.94%	12.02%	12.84%
16.33%	16.30%	16.32%	16.23%	16.32%	16.33%	16.32%	16.29%	16.32%	16.21%	16.31%
15.82%	15.44%	15.80%	14.60%	15.72%	15.63%	15.76%	15.51%	15.82%	14.95%	15.64%
13.32%	12.90%	13.32%	10.86%	13.08%	13.31%	13.07%	12.76%	13.32%	12.34%	13.07%
13.85%	13.56%	13.83%	12.64%	13.74%	13.78%	13.75%	13.56%	13.85%	13.01%	13.72%
12.57%	12.28%	12.56%	11.14%	12.42%	12.56%	12.41%	12.17%	12.56%	11.86%	12.39%
13.10%	13.10%	13.10%	13.10%	13.10%	13.10%	13.10%	13.10%	13.10%	13.10%	13.10%
15.94%	15.10%	15.91%	11.75%	15.54%	15.75%	15.55%	14.85%	15.93%	13.78%	15.48%
11.47%	10.88%	11.46%	8.12%	11.14%	11.41%	11.13%	10.68%	11.47%	10.16%	11.12%
11.76%	10.67%	11.67%	8.36%	11.47%	11.24%	11.58%	10.83%	11.75%	8.20%	11.36%
12.25%	10.34%	12.10%	6.04%	11.76%	11.21%	11.96%	10.66%	12.23%	7.94%	11.32%
10.98%	10.03%	10.90%	7.92%	10.74%	10.47%	10.84%	10.40%	10.98%	9.20%	10.51%
14.13%	11.89%	13.94%	6.85%	13.54%	13.15%	13.75%	12.30%	14.12%	6.47%	13.31%
10.50%	9.29%	10.40%	6.70%	10.19%	9.94%	10.30%	9.47%	10.50%	6.52%	10.06%
19.10%	18.84%	19.09%	17.74%	18.96%	19.10%	18.95%	18.81%	19.08%	18.56%	18.95%
11.83%	11.52%	11.81%	10.70%	11.73%	11.71%	11.75%	11.45%	11.82%	10.80%	11.69%
16.30%	16.14%	16.29%	15.71%	16.24%	16.29%	16.24%	16.02%	16.29%	15.73%	16.20%
14.57%	14.50%	14.56%	14.33%	14.54%	14.56%	14.54%	14.45%	14.56%	14.34%	14.52%
14.33%	14.16%	14.32%	13.68%	14.27%	14.32%	14.27%	14.03%	14.32%	13.64%	14.22%
11.91%	11.63%	11.90%	10.72%	11.80%	11.89%	11.80%	11.44%	11.90%	10.88%	11.74%
19.95%	19.07%	19.88%	17.04%	19.71%	19.50%	19.79%	19.17%	19.93%	17.92%	19.51%
14.38%	14.22%	14.37%	13.86%	14.33%	14.32%	14.34%	14.20%	14.38%	13.81%	14.31%
11.07%	10.87%	11.05%	9.70%	11.00%	11.07%	11.03%	10.66%	11.05%	9.56%	10.94%
12.50%	12.29%	12.48%	11.54%	12.44%	12.44%	12.46%	12.24%	12.49%	11.61%	12.39%
12.93%	12.25%	12.88%	9.40%	12.69%	12.81%	12.76%	11.95%	12.91%	9.56%	12.58%
17.65%	17.41%	17.64%	16.87%	17.56%	17.60%	17.56%	17.26%	17.64%	16.80%	17.51%
14.97%	14.59%	14.93%	13.64%	14.84%	14.97%	14.84%	14.64%	14.91%	14.01%	14.79%
14.46%	14.14%	14.45%	12.94%	14.32%	14.44%	14.33%	14.10%	14.45%	13.48%	14.30%

Source: Authors' calculations.

[33] In fact, high volatility may also increase the probability of switching from a high-liquidity regime to a low-liquidity regime, which is not captured in this paper due to the heavy computational burden associated with multivariate Markov regime-switching models.

V. CONCLUSIONS AND POTENTIAL EXTENSIONS

The paper develops an empirical approach to quantify haircuts on asset fire sales during stress and non-stress periods. Fire sales in stress periods could lead to statistically significantly higher price impacts on the assets that are sold compared to normal asset sales in non-stress periods. Literature has documented that price impact, as one of the measures for market liquidity, exhibits significant binary or regime-switching behavior. Based on this feature of market liquidity and the feedback loop between funding and market liquidity in stress tests, we assume that funding liquidity stress in systemic fire-sale events could trigger a regime shift in the market liqudity of the fire-sold assets. As our calculations show, fire sales of assets could lead to additional depletion of banks' capital.

The key component of our approach is the Markov regime-switching model, used to estimate haircuts on the fire-sold assets based on the collective amount of assets sold (as opposed to linear haircuts and individual fire-sale amounts). Instead of following the constant haircut assumption of most stress tests, we allow the haircuts on fire sales to change with the total amount of assets (in each asset class) that are sold by all banks at the same time. We argue that the estimated price impact in the stress regime is more suitable for systemic events, while that in the non-stress regime should be used for idiosyncratic events. Moreover, we also link the haircuts with market volatilities, both global and country-specific market volatilities, as market uncertainty could affect the regime of market liqudity according to the IMF (2015). By including market volatilities as additional regime-switching variables, the Markov regime-switching models allow us to simulate both stress-regime and non-stress-regime haircuts under different scenarios of market volatilities.

We applied the approach to euro area banks, and found that the estimated haircuts are highly non-linear and much higher during stress periods than during non-stress periods. This has important impolications for the haircuts used in stress tests. Given that the purpose of stress tests is to estimate the potential losses in stress periods, the haircuts estimated in stress periods seem to be more appropriate. The use of estimated stress-regime haircuts could significantly reduce banks' capital ratios compared to using non-stress haircuts. The magnitude of the reduction in capital ratios depends on the total amount of the assets that all banks fire-sell at the same time. Moreover, the results with market volatilities as additional regime-switching variables also suggest that using stress-regime haircuts could significantly reduce banks' capital ratios, with the size of the impact depending on both the total fire-sale amount as well as the scenario of market volatilities.

This approach can be incorporated into FSAP-style macroprudential stress tests as a module on the estimation of haircuts from (marketable) asset fire sales. More generally, it can also be used to model funding costs in stressful situations. For example, the 2017 Japan FSAP (IMF 2017) used a similar approach to model and project US dollar funding costs in the yen-US dollar swap market by capturing the regime-siwtching behavior of market liquidity (Appendix II, as well as IMF 2017).

For future work, several extensions of the framework could benefit the use of the model in practice. First, modeling the pecking order and sequencing the asset fire sales represent a challenge. In the case of a prolonged systemic crisis, where many banks are experiencing liquidity shortages, these banks may be willing to hoard liquidity and try to liquidate less liquid assets first. However, they may not be able to sell illiquid assets due to larger haircuts on these assets and a lack of demand. In the case of an idiosyncratic shock to a bank, the bank may be able to liquidate less liquid assets, although the signaling concern may prevent the bank from selling illiquid assets first. The pecking order also depends on the information and assumptions that markets have about the liquid (and unencumbered) assets of other banks.

Another challenge is the time horizon of fire sales. How much and under what prices is it possible to sell within the predefined time horizon in stress tests? It is obvious that market prices would fall more if financial institutions were to liquidate a large amount of assets in a very short time period compared to doing so in a longer time period. But this is not a typical behavior, as institutions prefer to sell smaller amount of securities to avoid significant changes in market liquidity and prices.

The model could also be extended to simulate the haircuts for fire sales triggered by non-bank financial institutions. Haircut estimations and their links with CARs represent just first-round stress effects observed in a financial system. One can refine the method to simulate effects of fire sales by non-bank financial institutions, such as money market mutual funds, insurance companies, and pension funds. Moreover, those institutions may play a stabilizing role by increasing demand for assets that banks would like to sell. It is also possible to extend the model by incorporating second-round effects of contagion among various financial institutions. Contagion may not be isolated to only price effects through asset valuations, but may also spread, for instance, across the network of bilateral exposures among banks. Ignoring these interbank feedback effects may lead to underestimation of losses. Halaj and Kok (2013) developed the model based on a range of possible interbank networks.

All in all, the number of market participants, their liquidity constraints and their cross-exposures are important features of a more general-equilibrium approach for stress tests. The reduced-form model presented in this paper could be used to calibrate a general-equilibrium model.

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APPENDIX I. MARKET LIQUIDITY MEASURES

Different measures of market liquidity from the price impact perspective at the security level have been developed in literature (IMF survey 2015). One widely used measure of the stock market liquidity is the Amihud (2002) measure, which is defined as the ratio between the absolute value of daily returns and daily trading volume of a frequently traded security. It shows the daily price change associated with one dollar of trading. Market depth captures the quantity dimension of market liquidity, that is, the ease with which one can trade securities in large amounts (IMF 2015). It is worth noting that the measure is typically used for frequently traded securities whose trading volumes are net zero, for example, stocks.

Another widely used indicator of market liquidity in literature that measures the impact of trading on prices is the price impact measure. More specifically, the security-level price impact measure (see, for example, Holden and others 2014 and IMF 2015) is defined as the slope coefficient of a regression of price change on a signed order flow (buyer-initiated trades minus seller-initiated trades). It measures how much impact a one-unit (net) trading volume could have on the price on average. In other words, it represents the marginal cost of trading an additional unit of quantity (Holden and others 2014). It is worth mentioning that this measure assigns “signs” to trades, making it more suitable for modeling the haircuts for asset fire sales. This is because most asset fire sales are seller- rather than buyer-initiated trades. Moreover, this measure can be calculated even if the security is less frequently traded than stocks (for example, bonds). Transaction-level data are needed to calculate the security-level price impact measure.

APPENDIX II. USE OF MARKET REGIME-SWITCHING MODELS TO OBTAIN STRESSED FUNDING COSTS

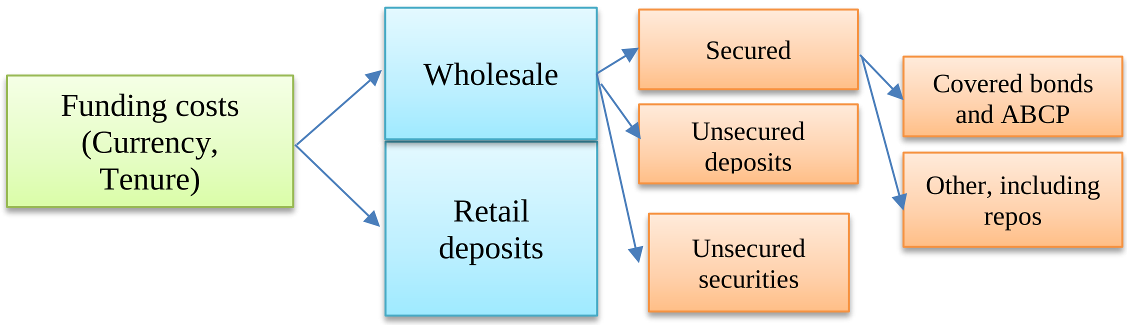
An interesting extension of the asset fire sales model is its links with the profitability-funding cost model. It is well known that a decline in CAR may increase banks' funding costs (Schmitz and Valderrama 2017; Barnhill and Schumacher 2011). Many of these models used linear regression techniques to come up with stressed funding costs. At the same time, funding costs exhibit non-linearity under stressed market conditions, thus the choice of non-linear models, such as Markov regime-switching regressions, would be an alternative. These assumptions were implemented by IMF staff in the case of liquidity-solvency stress tests conducted during the 2017 Japan FSAP (IMF 2017).

Solvency and liquidity shocks interact with each other and amplify each other's effect on banks' balance sheets, and result in much larger effects than those captured by pure solvency or liquidity stress tests. Therefore, it is important to integrate the key interactions between solvency and liquidity shocks observed during the GFC into a unified framework.

First of all, funding liquidity shocks triggered by a tightening in funding conditions, in either domestic or overseas markets, could lead to funding shortages in a traditional cash flow-based liquidity stress-testing framework.

Second, the tightening in funding conditions could lead to not only a shrinkage in the volume of funding, but also to an increase in the funding costs. Banks with a high share of asset encumbrance tend to have lower secured wholesale funding costs and higher funding costs on the unsecured part. As asset encumbrance increases, such banks most likely experience even higher funding costs or even close funding markets for the unsecured part. In particular, banks that have solvency concerns could experience a larger decline in available funding volume and a higher increase in funding costs. Solvency stress tests (for example, any balance sheet-based model) identify the weakest banks based on their capital adequacy after macrofinancial shocks in the adverse scenarios (the first round of simulation). The decline in capital adequacy in these particular institutions leads to higher funding costs and funding liquidity problems (for example, the closure of unsecured funding markets, higher withdrawals of wholesale deposits, additional margin calls for repos and derivatives due to higher counterparty risk, etcetera). Several recent papers have addressed the problem of linking funding costs with banks' solvency positions, especially endogeneity of funding costs and capital of the banks. For example, Schmitz and others (2017) analyze change in banks' funding costs for the 54 global banks. Their finding suggests that a 1 percent decrease in regulatory capital ratios leads to a decrease in funding costs of 1.05 percent. Higher funding costs also reduce the capital ratio (an increase of funding costs by 1 percent reduces CAR by 0.3 percent on average). Aymanns and others (2016) document that a decline in solvency ratios leads to higher unsecured funding costs, and decline in net interest margin. Overall, they find that a 1 percentage point decline in CAR leads to a 0.02 percentage-point increase in average funding costs, and a 0.04 percentage-point increase for wholesale funding costs.

To model the changes in funding the costs of banks' liabilities may be divided into multiple dimentions: funding costs in domestic currency and funding costs in foreign currency, and funding costs by tenure and type of instrument. In the absence of such data, one can use total funding costs as a ratio of interest expenses over interest rate-sensitive liabilities.



We used the Markov regime-switching models to calibrate shocks to funding costs of selected large Japanese banks. Large Japanese banks rely heavily on wholesale sources for foreign currency funding (Aldasoro and others 2018). The amount of banks' funding in US dollars accounts for less than 25 percent of their total funding in all currencies system wide. In contrast to their yen funding, most of banks' funding in US dollars comes from unsecured corporate funding, repos, and FX swaps. Although some of these have maturities longer than one year, a large share of them (particularly the FX swaps) are typically rolled over and repriced every three to six months.

This short repricing window of FX liabilities allows us to link liquidity pressures with a new price of funds in both USD and JPY during market-stress situations, and the evolution of banks' capital adequacy ratios.

Projections of US dollar funding cost capture the market liquidity stress in the USD/JPY swap market by using the Markov regime-switching model[34]. Since Japanese banks' US dollar funding relies heavily on FX swaps, any stress in the USD/JPY swap market could affect banks' US dollar funding cost. Our analysis on market liquidity indicates that the deterioration in the liquidity conditions in the USD/JPY swap market in 2016 increased the liquidity risk premium and pushed up the US dollar funding cost, despite some recovery in 2017[35]. This is mainly due to the observation that liquidity risk premium can change quickly when market liquidity stress occurs.

[34] The use of the Markov regime-switching models to identify the regimes of liquidity risk premium follows the work in Acharya and others (2013), IMF (2015), and Flood and others (2015).

[35] The "liquidity risk premium" is defined as the impact of market liquidity on US dollar funding cost.

The Markov regime-switching model can capture two main drivers of the change in market-wide US dollar funding cost, that is, developments in the three-month London Interbank Offered Rate (LIBOR) in USD (from the macroeconomic scenarios) and the liquidity stress in USD/JPY swap market[36]. In particular, it is assumed that there is no deterioration in market liquidity in the USD/JPY swap market in the baseline and moderate adverse scenario, and hence the main driver of the projected US dollar funding cost is the three-month LIBOR in US dollars. However, due to the more rapid tightening in US monetary policy, it is assumed that liquidity risk premium in the USD/JPY swap market switches from a tranquil regime to a stress regime in the severe adverse scenario, putting significant pressure on the US dollar funding cost.

In particular, following the October 2015 Global Financial Stability Report (IMF 2015), the following Markov regime-switching model is estimated for the change in USD funding cost, ΔFC_t^{USD}[37]:

$$\Delta FC_t^{USD} = \beta_0^k + \beta_1 \cdot \Delta LIBOR_t + \beta_2^k BAS_t + \varepsilon_t^k \tag{A1}$$

where *t* denotes time and *k* indicates the liquidity regime. $\Delta LIBOR_t$ is the change in the 3-month LIBOR in USD, and BAS_t is the bid-ask spread of the three-month USD/JPY swap contract—a measure of market liquidity, and is the only regime-switching variable in model (3), except the constant, β_0^k, which is also allowed to vary across regimes.

[36] Since most of the FX swap contracts that banks use are rolled over and repriced every three to six months, the three-month LIBOR in US dollars is used in the modeling.

[37] The USD funding cost is calculated from the three-month USD/JPY swap cost.

Appendix III. Program and Templates for Haircut and CAR Estimation

The proposed framework consists of two elements: (1) a Matlab-based program for haircut estimation using trading data; and (2) an Excel tool for market haircut calculation based on an aggregate amount of assets sold and CAR estimation.

I. MATLAB PROGRAM

The attached Matlab programs estimate the Markov regime-switching models (1) and (6) with regime-switching variances. The programs are built upon the Matlab package for Markov regime-switching models, that is, the MS_Regress package developed by Perlin (2014). The other two specifications, described in Section IV, with non-regime-switching variances can be easily estimated using the built-in package on Markov regime-switching models in the Stata software.

II. THE EXCEL TOOL

The Excel tool has multiple tabs, namely:

1. **Results_Stressed** tab provides a summary of stress testing results (CAR before and after liquidity shock and difference *vis-á-vis* no shock) in a form of a heatmap (bank-by-bank) and by each type of model (the version can calculate haircuts for up to 12 models, and it is easily expandable). The tab also provides a summary of haircuts on assets based on the amount of securities banks sell collectively (in percentages from 100 million value of securities sold).

2. **Charts tab:** produces Box-Whisker charts for banks' CAR.

3. **Stress parameters tab:** a user needs to input a selected number of scenario parameters, which are further divided into the following sub-categories:

   a) Liquidity stress input: the percentage of assets sold by each bank, and each type of security and the residual maturity of securities. This technically can be expanded for each type of security provided that the stress tester has data about holdings and daily trading data of these securities;

   b) Assumptions about revaluation of bonds: if "Yes" is selected, all bonds, no matter the accounting treatment (that is, AFS, HFT, HTM, FVPL, FVOCI, FVAC), are repriced using new haircuts; if "No" is selected, only AFS, HFT, FVPL, FVOCI are repriced;

   c) Assumptions about implementation shortfall parameter: default value is 50 percent, however, the stress tester can choose any value between 0 and 100;

d) Scenarios: linking haircuts with market volatility. The user has an option to generate stressed haircuts conditional on market volatility. The current version takes into account only one stressed period; however, the model is easily extendable to incorporate multiple periods. Two types of volatility data may be entered: global VIX (US) and country VIX, as residuals of the VIX equation, which links each country VIX with US VIX (an alternative to this approach would be to regress each country VIX with haircuts on securities, then US and countries' VIX shocks scenarios may be treated as independent).

4. **Haircuts_regressions tab:**an input tab for haircuts, estimated using various econometric models. The user can enter data for haircuts obtained from up to 12 different models.

5. **Exposures tab:** with this tab, the stress tester enters data about banks' exposures to securities.

6. **Scenario1_VIX and Scenario2_VIX tabs:** calculate haircuts based on VIX scenarios. No user input is needed.

7. **CAR_data tabs (before shocks and 1-12):** calculate CAR data used for Box-Whisker charts. No user input is needed.

8. **Total_amount_sold tab:** calculates the amount of securities sold by all banks. This tab also calculates the amount of securities left on the balance sheet (this information is later used to reprice these securities under new stressed haircuts). No user input is required.

9. **CAR tab:** calculates the capital adequacy ratio before shocks and for each model. The stress tester enters total assets, liabilities, capital, and RWAs data for each bank.