Online Annex 1.1 Technical Note[1]

A. Financial Conditions Indices[2]

The original methodology underpinning the Financial Conditions Indices (FCIs) used in Chapter 1 of this report was developed in the April 2017 GFSR and was applied, with some modifications, to the growth-at-risk estimation in the October 2017 GFSR. That methodology has been simplified to enable the computation of regional aggregates, and the identification of the contributions of underlying FCI components to the country aggregate FCIs.

Economy Coverage

The sample of economies for which FCIs were constructed includes the 29 systemically important jurisdictions in the IMF's Financial Sector Assessment programs, as well as the original FCI sample of 21 economies and the top 20 constituents of the EMBIG index (Figure A.1).

Figure A.1. Economy Coverage

Final sample	AE/EM	FSAP SIJ	original FCI group	Final sample	AE/EM	FSAP SIJ	original FCI group	EMBIG-20
Australia	AE	1	1	Argentina	EM			1
Austria	AE	1		Brazil	EM	1	1	1
Belgium	AE	1		Chile	EM		1	1
Canada	AE	1	1	China	EM	1	1	1
Denmark	AE	1		Colombia	EM			1
Finland	AE	1		Egypt	EM			1
France	AE	1	1	Hungary	EM			1
Germany	AE	1	1	India	EM	1	1	
Hong Kong SAR	AE	1		Indonesia	EM		1	1
Ireland	AE	1		Kazakhstan	EM			1
Italy	AE	1	1	Lebanon	EM			1
Japan	AE	1	1	Malaysia	EM			1
Korea	AE	1	1	Mexico	EM	1	1	1
Luxembourg	AE	1		Nigeria	EM			1
Netherlands	AE	1		Peru	EM			1
Norway	AE	1		Philippines	EM			1
Singapore	AE	1		Poland	EM	1		1
Spain	AE	1	1	Russia	EM	1	1	1
Sweden	AE	1	1	South Africa	EM		1	1
Switzerland	AE	1	1	Turkey	EM	1	1	1
United Kingdom	AE	1	1	Ukraine	EM			1
United States	AE	1	1	total	43	29	21	20

Sources: Bloomberg Financial L.P.; and IMF staff estimates.

[1] This is an annex to Chapter 1 of the October 2018 *Global Financial Stability Report*.

[2] This section was prepared by Sergei Antoshin, Yingyuan Chen, and Martin Edmonds.

FCI Components

Under the revised framework, the FCI components are similar to the price-of-risk FCI components presented in the October 2017 GFSR (Figure A.2). There, however, have been some changes: sovereign and corporate spreads on local debt for EMs were added to capture additional EM vulnerabilities; realized equity volatility was replaced with implied volatility based on option prices (such as the VIX), where available to derive a more forward-looking signal; and the variables for equity and house prices were adjusted to ensure greater consistency with other variables, and to reflect that the FCI measures the level—rather than the change—in financial conditions.

Figure A.2. Financial Conditions Index (FCI) Components

Variable	Measurement	US, Germany	Other AE	EM	Presence in the Oct 2017 GFSR
real short-term interest rate	3 month T-bill yield minus CPI yoy	1	1	1	+
interbank spread	Interbank rate (Libor) minus T-bill yield	1	1	1	+
term spread	5-year govt bond yield minus T-bill yield	1			+
sovereign local debt spread	5-year yield minus US or Germany yield		1	1	+ for AE
sovereign dollar debt spread	EMBI spread			1	+
corporate local currency spread	ICE OAS	1	1	1	+ for AE
corporate dollar debt spread	CEMBI spread			1	+
equity prices	MSCI P/B	1	1	1	+ (qoq)
equity vol	VIX/V2X/VNKY	1			+ all
exchange rate	debt-weighted exchange rate			1	+ (vis-à-vis USD)
real house prices	BIS house prices yoy minus CPI yoy	1	1	1	+ (qoq)

Source: IMF staff estimates.

FCI Weights

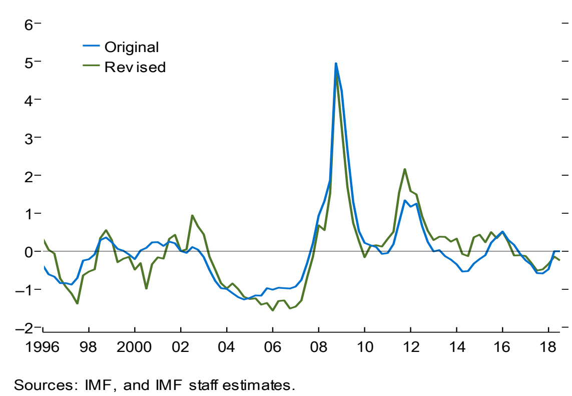
The time-varying weights based on a dynamic factor model from the original methodology were replaced with fixed weights from a principle component analysis. This adjustment has improved the tractability of the exercise, simplified the computation of the contributions of FCI drivers, and helped ensure parameter stability during updates.

Aggregation

In the original methodology, a PCA-based estimation on the full sample of country-level FCIs was used to construct the global FCI. Under the revised methodology, PPP GDP weights were employed instead. An important advantage of using this method is that it allows additivity of countries to the regional aggregates and from regions to the global total.

Figure A.3. Global Price-of-Risk FCI

(Standard deviation from mean, 1996:Q1- 2018:Q3)



Sources: IMF and IMF staff estimates.

These methodological revisions have resulted in relatively small changes to the global FCI, though the revised FCI better captures abrupt changes in its components (Figure A.3).

B. Capital-Flows-at-Risk[3]

The Capital-Flows-at-Risk framework takes a forward-looking perspective on risks to emerging market (EM) capital flows by asking what global financial conditions today can tell us about the expected future distribution of capital flows. In particular, we use a quantile regression framework that allows us to quantify the downside (and upside) risks to future capital flows, conditional on the prevailing global financial conditions. This approach is similar in spirit to recent analysis on Growth-at-Risk, published in the Global Financial Stability Report (IMF 2017 and 2018; see also Adrian et al. 2018a). The framework also allows us to analyze whether the drivers of an inflow surge are different from those of a capital flows reversal.

Our approach differs from the existing literature in that previous work on the drivers of capital flows focused almost exclusively on the contemporaneous relationship between drivers and flows. By contrast, we look at the current drivers of future capital flows over "near term" and "medium term" time horizons. Combining the forward-looking approach with quantile regressions – an approach only few studies have used (e.g., Ghosh et al. 2014) – allows us to gain insights about the expected future probability distribution of capital flows. From a policy perspective, this framework provides a risk assessment for capital flows that can help policymakers prepare for future reversals and surges of capital flows.

Data

The analysis focuses on portfolio debt flows. The dependent variable is gross portfolio debt inflows, i.e., net non-resident purchases of EM debt instruments. We use quarterly balance of payments data from 1997Q2 to 2017Q4 for about 60 emerging market and developing countries, based on the IMF's Financial Flow Analytics database. Portfolio flows data are measured in US dollars, scaled by EM GDP and aggregated across countries (Figure B.1).[4] For the purpose of this analysis, we define a "medium-term" time horizon as the period from 5 to 8 quarters ahead, averaging inflows as a share of EM GDP over these four quarters. In the GFSR, we also report results for a "near-term" time horizon, defined as average flows over the current and the next two quarters.

The independent variables in the analysis capture the various external and domestic drivers ("push and pull" factors) that have been established in the capital flows literature (see Koepke 2015 for a literature survey). In our preferred specification, push factors include measures of investor risk aversion, proxied by: (i) the US BBB-rated corporate bond spread; (ii) market interest rates (US 10-

[3] This section was prepared by Rohit Goel and Robin Koepke.

[4] China is excluded from this analysis because of its unique country characteristics, including its size relative to the rest of EMs.

year Treasury yields[5]); and (iii) the US dollar (measured by the DXY dollar index).[6] On the domestic side, we include real GDP growth in emerging market economies (excluding China) as a control variable to account for economic conditions in recipient countries. We also include lagged inflows (over the preceding four quarters) and a constant term.

Model specification

We follow the empirical approach used for Growth-at-Risk in Adrian et al. (2018b). We denote y_{t+h} as the average portfolio debt inflows to emerging and developing countries (in % of GDP) between t and h, while x_t is a vector of independent variables. In a quantile regression of y_{t+h} on x_t, the regression slope δ_α is chosen to minimize the quantile weighted absolute value of errors:

(1) $\hat{\delta}_\alpha = \text{argmin} \sum_{t=1}^{T-h} \left(\alpha . 1_{y_{t+h} > x_t \delta} |y_{t+h} - x_t \delta| + (1-\alpha) . 1_{y_{t+h} < x_t \delta} |y_{t+h} - x_t \delta|\right)$

where $1_{(\cdot)}$ denotes the indicator function. The predicted value from that regression is the quantile of y_{t+h} conditional on x_t.

(2) $\boldsymbol{\hat{Q}}_{y_{t+h} > x_t}(\boldsymbol{\alpha}) = x_t \hat{\delta}_\alpha$

We obtain an empirical distribution for predicted capital flows by considering the range of quantiles from the first to the 99th percentile. We then define capital flows-at-risk (CaR), the value at risk of future capital flows, by

(3) $\Pr\left(y_{t+h} \le CaR_h(\alpha | \Omega_t)\right) = \alpha$

where $CaR_h(\alpha | \Omega_t)$ captures capital-flows-at-risk for our group of emerging market and developing economies h quarters in the future at a α probability. For a low value of α, CaR will capture the expected inflows at the lower end of the capital flows distribution. We define CaR to be the lower 5th percentile of the capital flows distribution, meaning that there is 5 percent probability that capital flows would be lower than CaR.

[5] In the empirical literature, the change in US 10-year Treasury yields is commonly used to analyze the determinants of capital flows. The predictive content for *future* capital flows, however, is better captured by the *level* of 10-year yields. We de-trend the 10-year yield using a Hodrick-Prescott filter to remove the secular downward trend observed over the past 35 years. The de-trended variable can be interpreted as a cyclical measure of US interest rates, with yields generally rising during economic expansions and falling during contractions.

[6] A broad range of additional explanatory variables were also tested, such as alternative measures of US interest rates (e.g., market-implied expectations of the federal funds rate and the slope of the US yield curve, which had lower statistical significance), risk aversion (the VIX index of implied US equity volatility, which yielded similar results to the BBB spread), and the dollar (the real effective exchange rate, which yielded very similar results to the DXY index). Other variables that do not seem to have significant predictive content include measures of commodity prices (the Brent oil price; Bloomberg's commodity price index), an EM exchange rate index, US growth, and the size of the Fed's balance sheet. The Fed balance sheet plays an important role in a separate model used in the GFSR to analyze capital flows, but for the purpose of the capital flows at risk analysis the time period over which quantitative easing has been used as a policy tool is relatively short.

The estimates reported for the 5th percentile are directly taken from the quantile regressions. In addition, we show probability density functions obtained by mapping quantile regression estimates into a smoothed distribution. We consider a range of distributions and report results for the Gaussian (normal) distribution.

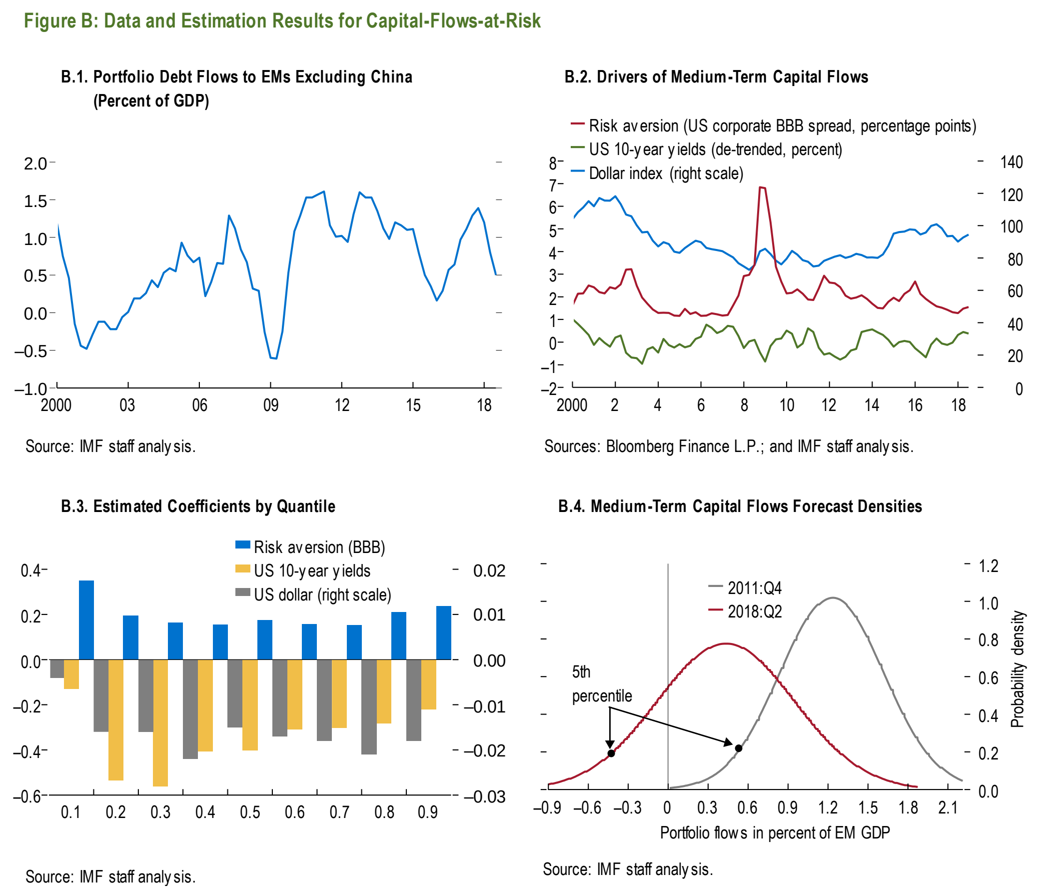
Results

The results suggest that there are three main factors that have predictive power for medium-term portfolio debt flows to EMs: investor risk appetite, US long term interest rates, and the US dollar (Figure B.2). Higher US interest rates and a stronger US dollar are associated with weaker inflows, both contemporaneously and in the medium term, consistent with the empirical literature. Stronger risk appetite is associated with greater inflows contemporaneously, but predicts weaker inflows in the medium term. This finding may partly be explained by mean-reversion patterns in the risk appetite variable; for example, periods of investor caution are followed by periods of greater investor confidence.

These results can usefully be applied to extreme movements in capital flows, often referred to as surges (i.e. large inflows) and reversals (defined here as flows below zero, i.e. net outflows). The results suggest that future reversals and, to a lesser extent, surges of capital flows are disproportionately explained by investor risk aversion, as reflected in higher coefficient estimates at the lowest and highest quantiles (Figure B.3). By contrast, US interest rates and the dollar seem to have less predictive power for capital flow reversals (which are typically observed at the lowest percentiles of the capital flow distribution).

The results suggest that downside risks to medium-term capital flows are currently high, driven by relatively elevated US interest rates, a strong dollar, and buoyant risk appetite. We estimate that medium-term capital flows at risk of 0.6 percent of the combined GDP of EMEs (excluding China), on par with the Global Financial Crisis (also measured over a four-quarter period). This is much less benign than, for example, in late 2011:Q4, at the height of the European sovereign debt crisis, when US interest rates were low, the dollar was weaker, but the risk aversion was high (Figure B.4).

Figure B. Data and Estimation Results for Capital-Flows-at-Risk



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C. Bank Solvency Simulations[7]

One way to assess forward-looking bank solvency is to use a simulation.[8] The simulations work by estimating stress capital ratios in the following year, using current balance sheets and a distribution of changes in the level of capital estimated from historical distributions of bank profitability.

In this report, the simulations are run on the consolidated balance sheets of a sample of about 600 banks headquartered in advanced economies, though the size of the sample varies over time as banks merge, new banks are started, or as banks fail (Table C.1).

Table C.1. Bank Sample

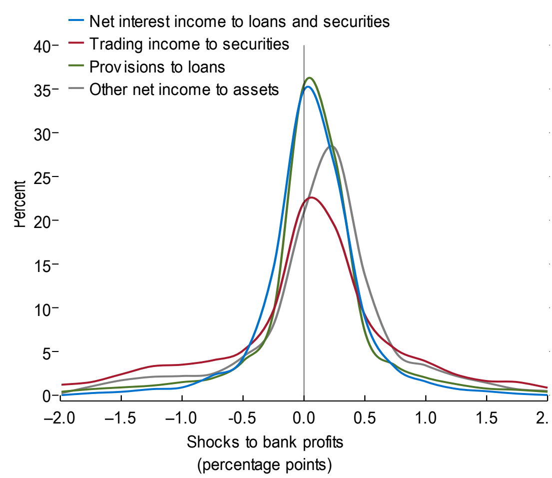
Euro area (175 banks)		Other Europe (65 banks)	Asia and Pacific (105 banks)
Austria	Luxembourg	Denmark	Australia
Belgium	Malta	Norway	Japan
Cyprus	Netherlands	Sweden	Korea
Finland	Portugal	Switzerland	New Zealand
France	Slovenia	United Kingdom	Singapore
Germany	Slovakia		
Greece	Spain		**North America (260 banks)**
Ireland			Canada
Italy			United States

Source: IMF staff.

Method

The distributions of bank profitability are based on historical data from 1990 onwards. Profits are divided into four categories, all calculated as a percentage of a relevant item on the balance sheet, so that rates of profit can be applied to banks with different balance sheet sizes and various mixes of business. The categories are: (i) net interest income to loans and securities; (ii) trading income to securities; (iii) provisions to gross loans; and (iv) other net income to assets.

Figure C.2. Distributions of Bank Profitability



Sources: Bloomberg L.P.; and IMF staff analysis.

Given that the method applies historical data to estimate profits in a future time period, and that profits vary with the economic cycle, shocks to each of the profitability categories were calculated (i.e., the change in profitability from one year to the next) as

[7] This section was prepared by Will Kerry.

[8] Stress tests are also a forward-looking assessment of bank solvency.

shown in Figure C.2. Furthermore, ten different distributions were calculated for each profit category, based on the current level of profitability at the time, to reflect the possibility that changes in profits may also be a function of the stage in the economic cycle (e.g., to capture if a bad year tends to be followed by a good year).

The simulations work by taking 10,000 draws from the profitability distributions for each bank. These shocks are multiplied by the relevant balance sheet item and added to current profits to obtain estimates of profits in the following year. The bank is assumed to pay dividends at the same rate as the current year if it makes a profit, and no dividends if it makes a loss. Retained earnings are then added to current capital to estimate capital at the end of the next year. It is assumed that the average risk weight of assets remains the same as in the current year. The simulations are run for each year since 2006, using the balance sheet, income and profitability distributions at that point in time.

The estimated capital of each bank in each simulation is tested against two thresholds: a Tier 1 ratio of 4.5 percent; and a leverage ratio of 3 percent. For the GSIBs, the capital surcharges are added to the Tier 1 ratio threshold. Each simulation where a bank's capital ratio falls below either threshold is counted. This then allows an estimated probability of a capital need over the following year. The same capital ratio thresholds are used over time so that the results can be compared, though these thresholds are higher than the regulatory ratios in place in the pre-crisis and crisis years. The results are presented in terms of the proportion of sample banks (by assets) with a probability of a capital need that is 20 percent or higher in the simulations.

Conclusion

This method allows a forward-looking assessment of bank solvency as an alternative to simply assessing current capitalization in banks. Of course, stress tests also provide a forward-looking assessment and this method is certainly not intended to be a substitute for the much more detailed work that goes into a stress test of banks. However, this method does provide a useful risk assessment of bank capitalization, based on historical experience. The method is particularly useful when stress tests have not been conducted recently, or when comparable stress tests are not available across banking sectors in different countries.

D. Jump Risk[9]

Market microstructure has undergone a significant shift over the last few years, driven by regulation, evolving balance sheet capacities of financial intermediaries, as well as an increase in algorithmic trading. While numerous daily aggregate liquidity measures continue to indicate relatively benign conditions, the analysis considers implications of such conditions on asset price dynamics at high frequency, using intraday data. The aim here is to gauge the extent to which microstructure changes may be systematically impacting the nature of intraday price evolution.

Methodology

It is assumed that log asset price $Y(t)$ evolves according to the following (semimartingale) process such that:

$$dY(t) = \underbrace{\mu(t)dt}_{\text{drift}} + \underbrace{\sigma(t)dW(t)}_{\text{continuous component}} + \underbrace{JUMPS(t)}_{\text{discontinuous component}}. \qquad (1)$$

Here, the logarithmic price increment, $dY(t)$, is a function of a drift term, a continuous component and a discontinuous component. The continuous component is composed of standard Brownian motion $W(t) \sim \text{iid } N(0,1)$, scaled by a stochastic volatility process $\sigma(t)$. This continuous (diffusive risk) component generates 'smooth' price movements, characteristic of efficient incorporation of market information. The inability of prices to rapidly adjust to evolving information flow reveals itself as discontinuities, or jumps, in the price process. Jumps can in turn be further decomposed into two parts, as follows:

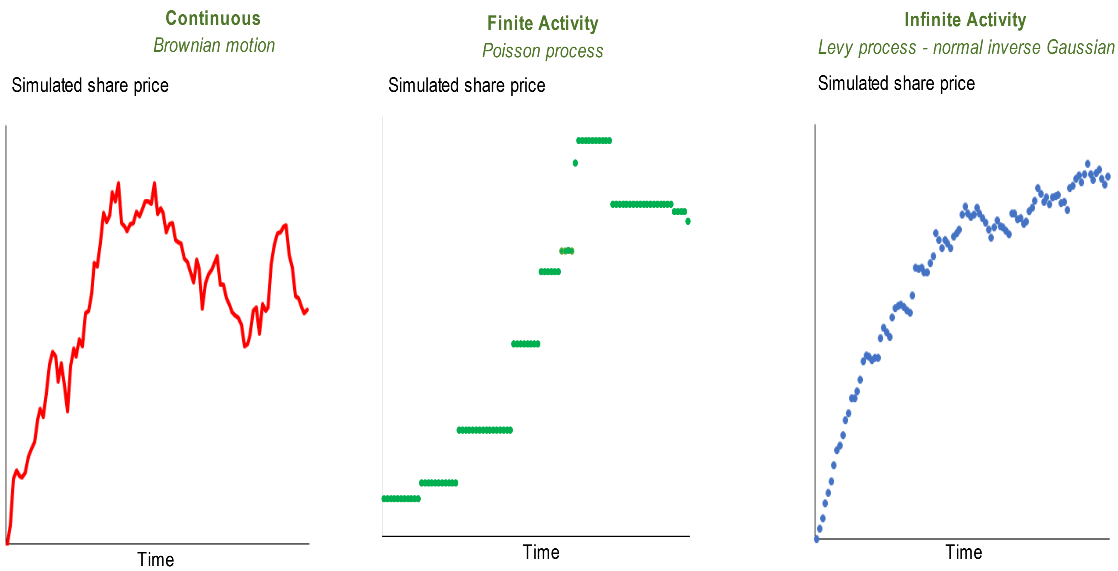
$$JUMPS(t) \coloneqq \underbrace{large\ jumps\ (t)}_{\text{finite activity}} + \underbrace{small\ jumps(t)}_{\text{infinite activity}}. \qquad (2)$$

Large (finite activity) jumps are considered rare events, related to significant news; whereas small, but frequent (infinite activity) jumps, are a result of limited ability of the market to absorb large transactions without price impact. From a distributional perspective, large jumps obey a Poisson process. Small jumps are well characterized by a Levy family of jump processes, of which Cauchy and Normal Inverse Gaussian, for instance, are members (Figure D.1).

The analysis conducted follows the methodology put forth in Ait-Sahalia and Jacod (2012) (see also Erdemlioglu et al., 2013), focusing on a series of tests to gauge the prevalence of the different components in equation (1), over the course of a trading day. Using high frequency data these tests are based around a single metric, i.e., 'truncated power variation,' constructed using intraday price increments.

[9] This section was prepared by Rohit Goel, Piyusha Khot, and Sheheryar Malik.

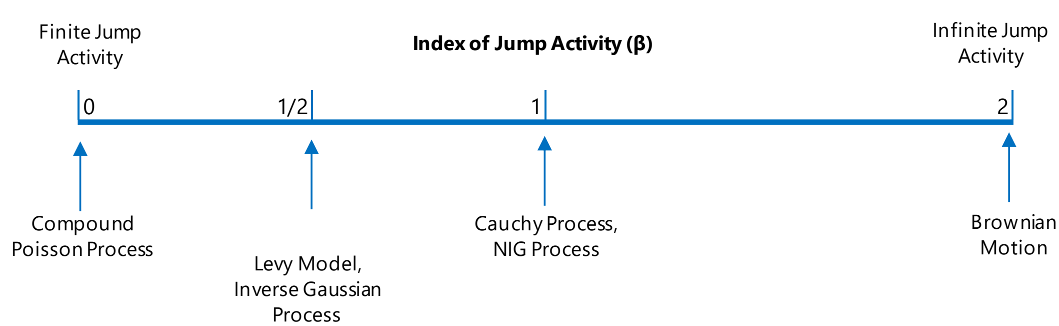
Figure D.1. Example: Simulated Price Paths



Source: IMF staff.

Importantly, tests under consideration can identify what type of jumps are likely present in the data (finite or infinite), but are not informative about intensity of jump activity. For this purpose, an index of jump activity (the Blumenthal-Geetor Index) can be constructed to describe in more specific terms the process of price jumpiness (Figure D.2). Finite activity jumps reside at one end of the spectrum, and Brownian motion at the other.

Figure D.2. Index of Jump Activity



Sources: Ait-Sahalia and Jacod (2012); and IMF staff.

But before attempting to disentangle the various components in equations (1) and (2), a high-level analysis is conducted in which jumps correspond exclusively to a finite activity assumption. Disentangling continuous components and finite activity jumps has been considered by *inter alia* Barndoff-Nielsen and Shephard (2006), and Andersen et al. (2007). Statistically significant jumps are identified using the test proposed by Huang and Tauchen (2005). The relative proportion of daily price variation attributable to continuous component and jump component is tracked over time, with the intensity of jumps defined as number of significant jump days per month.

Data

In this analysis, we focus on intraday pricing data for the S&P 500 Index recorded at 15, 30 and 60 second time intervals, starting in January 2009. The data are truncated to include only prices recorded between 9.30 AM and 4.00 PM. While the focus of the analysis is on the overall index, individual economic sector components of the S&P 500 were also analyzed. This component level analysis was run using pricing data starting in January 2018.

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