A Real-Time Proxy for the Global Financial Cycle

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September 23, 2025

Abstract

This note details the construction of a real-time, open-source proxy for the Global Financial Cycle (GFC) measure of Miranda-Agrippino & Rey [2020]. Following Habib & Venditti [2019], I employ a dynamic panel of 57 national and sectoral stock market indices and extract a common factor that captures the co-movement in global financial conditions. The proxy is updated weekly and provides a timely indicator for researchers and practitioners.

1 Motivation

The Global Financial Cycle (GFC) describes the common co-movement of gross capital flows, asset prices, and credit growth across countries. As documented by Miranda-Agrippino & Rey [2020], a significant portion of this variation can be captured by a single global factor. This project provides a transparent, open-source, and automatically updated proxy for this factor using publicly available data, offering a real-time view of global financial conditions based on the methodology of Habib & Venditti [2019]¹.

2 Data

The proxy is constructed from a panel of 57 national and sectoral stock market indices sourced from Stooq.com. A static list of major world indices, found in the indices_list.txt file in the project's repository, is used to ensure consistency across updates. The list and some descriptive statistics are also shown in 1. The script downloads daily closing prices for each index starting from 2002. The full dataset and replication code are available at https://github.com/iweigandi/daily-global-financial-cycle-proxy.

¹See also Davis & Zlate [2023], Aldasoro, Hördahl & Zhu [2022].

3 Methodology

The Global Financial Cycle (GFC) proxy is constructed as the first principal component (PC1) from a panel of national and sectoral stock market index returns. In this section I provide the rationale for working with national and sector-level indices, following the intuition in Habib & Venditti [2019].

3.1 Model Specification

The benchmark framework is the dynamic factor model of Miranda-Agrippino & Rey [2020], which is estimated on a large cross-section of individual asset returns. In their formulation, the return on asset i in country j at time t is decomposed into a global factor, a country-specific factor, and an idiosyncratic shock:

$$r_{i,j,t} = \lambda_i f_t^{\text{global}} + \lambda_{i,j} f_{j,t} + \xi_{i,j,t}. \tag{1}$$

By contrast, the approach of Habib & Venditti [2019] works with country-level averages of returns, rather than individual assets. This leads to a simplified specification:

$$r_{j,t} = \lambda_j f_t^{\text{global}} + \xi_{j,t}. \tag{2}$$

Equation (2) shows that country-level returns load directly on the same global factor f_t^{global} as in the full model, but without the additional country factor $f_{j,t}$. As argued by Habib & Venditti [2019], regional or national averages provide a consistent estimate of the global factor, since they aggregate idiosyncratic components while preserving the common exposure to f_t^{global} . Thus, modeling national indices rather than thousands of individual assets is a valid and tractable alternative for extracting the GFC.

3.2 Proxy Construction

Two versions of the proxy are calculated:

- Monthly Proxy: The PC1 is extracted from the panel of monthly log-returns.
- Daily Proxy: PC1 is extracted from a panel of 21-day moving averages of daily log-returns.

4 Results

The dataset includes a balanced panel of 57 national and sectoral stock market indices. From this panel, I extract both monthly and daily versions of the Global Financial Cycle (GFC) proxy.

Figure 1 plots the daily and monthly proxies alongside the GFC factor of Miranda-Agrippino & Rey [2020], illustrating their strong co-movement and the ability of the real-time proxy to track global financial conditions reliably.

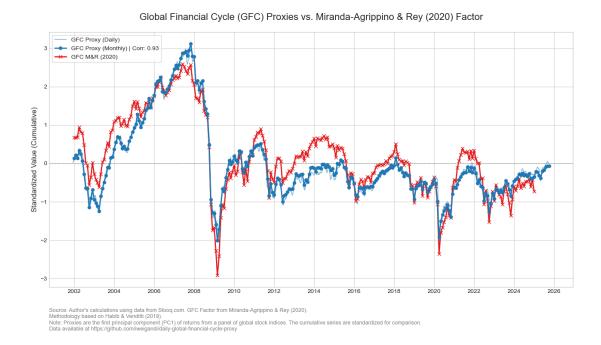


Figure 1: Daily & Monthly GFC Proxies vs. GFC factor of Miranda-Agrippino & Rey [2020]

For the **monthly proxy**, the first principal component explains 46.6% of the total variance in stock market returns. The **daily proxy**, constructed from 21-day moving averages of daily returns, explains a slightly higher share of the variance at 49.5%. Both proxies, therefore, capture a substantial portion of the common variation across countries. The countries' loadings on the common factor are shown in 1.

The monthly proxy achieves a correlation of 0.93 with the GFC factor of Miranda-Agrippino & Rey [2020] series and a mean squared error (MSE) of 0.16, indicating that it reproduces the benchmark factor closely while being updated in real time. The daily proxy shows a similar degree of fit.

References

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Appendix



Table 1: Summary Statistics and Factor Loadings of Monthly Returns

Country	Index	Symbol	Count	Mean	Std	Min	25%	50%	75%	Max	Factor Loading
Argentina	MERVAL	MRV	286	0.0318	0.1167	-0.5359	-0.0378	0.0311	0.1014	0.3967	0.2127
Russia	RTS	RTS	286	0.0053	0.0948	-0.4491	-0.0490	0.0118	0.0644	0.2668	0.2114
Greece	ATHEX COMP	ATH	286	-0.0010	0.0826	-0.3267	-0.0386	0.0077	0.0488	0.2577	0.1996
Iceland	ICEX	ICEX	286	0.0022	0.0946	-1.2555	-0.0193	0.0117	0.0378	0.1643	0.1661
Germany	TECDAX	TDXP	286	0.0038	0.0687	-0.3676	-0.0281	0.0104	0.0446	0.2446	0.1658
Turkey	XU100	XU100	286	0.0161	0.0852	-0.2629	-0.0434	0.0226	0.0705	0.2603	0.1638
Russia	MOEX	MOEX	286	0.0090	0.0735	-0.3570	-0.0267	0.0147	0.0534	0.1993	0.1612
Romania	BET	BET	286	0.0116	0.0753	-0.4142	-0.0152	0.0131	0.0472	0.2977	0.1594
Germany	MDAX	MDAX	286	0.0068	0.0562	-0.2343	-0.0245	0.0124	0.0438	0.2290	0.1567
Italy	FTSE MIB	FMIB	286	0.0010	0.0591	-0.2541	-0.0314	0.0069	0.0366	0.2066	0.1563
Hungary	BUX	BUX	286	0.0092	0.0620	-0.3344	-0.0224	0.0153	0.0446	0.1835	0.1547
Brazil	BOVESPA	BVP	286	0.0085	0.0672	-0.3553	-0.0330	0.0088	0.0580	0.1648	0.1531
Germany	DAX	DAX	286	0.0054	0.0569	-0.2933	-0.0229	0.0131	0.0381	0.1937	0.1524
Germany	SDAX	SDXP	286	0.0068	0.0544	-0.2331	-0.0189	0.0139	0.0407	0.1706	0.1504
Norway	OSE	OSEAX	286	0.0088	0.0532	-0.2736	-0.0165	0.0129	0.0413	0.1402	0.1451
Netherlands	AEX	AEX	286	0.0022	0.0524	-0.2262	-0.0223	0.0091	0.0342	0.1457	0.1432
Spain	IBEX35	IBEX	286	0.0021	0.0558	-0.2512	-0.0220	0.0070	0.0316	0.2246	0.1427
Czech Republic	PX	PX	286	0.0062	0.0552	-0.3165	-0.0180	0.0101	0.0405	0.1711	0.1413
Bulgaria	SOFIX	SOFIX	286	0.0084	0.0725	-0.4763	-0.0169	0.0043	0.0405	0.2512	0.1403
South Korea	KOSPI	KOSPI	286	0.0059	0.0556	-0.2631	-0.0232	0.0091	0.0401	0.1337	0.1400
India	SENSEX	SNX	286	0.0113	0.0602	-0.2730	-0.0206	0.0108	0.0482	0.2489	0.1389
Finland	HEX	HEX	286	0.0010	0.0547	-0.2035	-0.0273	0.0053	0.0342	0.1977	0.1387
France	CAC40	CAC	286	0.0020	0.0498	-0.1923	-0.0272	0.0089	0.0328	0.1833	0.1378
USA	NASDAQ COMP	NDQ	286	0.0086	0.0533	-0.1906	-0.0191	0.0143	0.0425	0.1436	0.1374
USA	NASDAQ100	NDX	286	0.0096	0.0557	-0.1716	-0.0203	0.0156	0.0479	0.1728	0.1372
Belgium	BEL20	BEL20	286	0.0020	0.0487	-0.2409	-0.0197	0.0095	0.0330	0.1865	0.1354
Hong Kong	HANG SENG	HSI	286	0.0030	0.0602	-0.2545	-0.0293	0.0095	0.0372	0.2360	0.1351
UK	FTSE250	FTM	286	0.0046	0.0478	-0.2469	-0.0180	0.0078	0.0345	0.1665	0.1338