# FTSE/JSE Listed Property: Investigating Time-Varying Correlations Using a DCC MV-GARCH Model

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## 1. Introduction

Investors tend to diversify components of their investment portfolios to property assets to mitigate their portfolio's downside risk. In addition, listed property securities are attractive as they generally yield high dividends and showcase potential moderate long-term capital appreciation. However, in the past decade, FTSE/JSE-listed property securities have performed weakly and have become significantly more volatile. Moreover, the correlation between FTSE/JSE-listed property securities and alternative financial assets has become more positive, placing its diversification benefits under scrutiny (Carstens & Freybote, 2020; Ijasan, Tweneboah & Mensah, 2017; Oberholzer & Venter, 2015).

To this extent, this project investigates time-varying conditional correlations between FTSE/JSE-listed property securities and the broader FTSE/JSE assets by adopting the parsimonious Dynamic Conditional Correlation (DCC) Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MV GARCH) modelling procedure.

To do so, I construct a market capitalisation-weighted portfolio of all the FTSE/JSE-listed property constituents, dubbed PROP, and compare its time-varying conditional correlations with the JSE Small Cap Index (SMLC(J202)) and Shareholder Weighted Index (SWIX(J433)). The self-constructed PROP index closely imitates the JSE The FTSE/JSE All Property Index (J803), however, also includes all small-and-medium-cap constituents. The indexes' cumulative returns, together with the JSE Top 40 Index (Top40(J200)), are shown in Figure 1.1 below.[3] The PROP index performance has weakened and becomes increasingly unstable in the recent decade, amplified during recessionary periods (blue-shaded area).

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*This project was generated using Katzke (2017), a package to create Elsevier templates for Rmarkdown.*

[3] All indexes' weighting is capped at 10%, except for the SMLC(J202), which is capped at 15%.

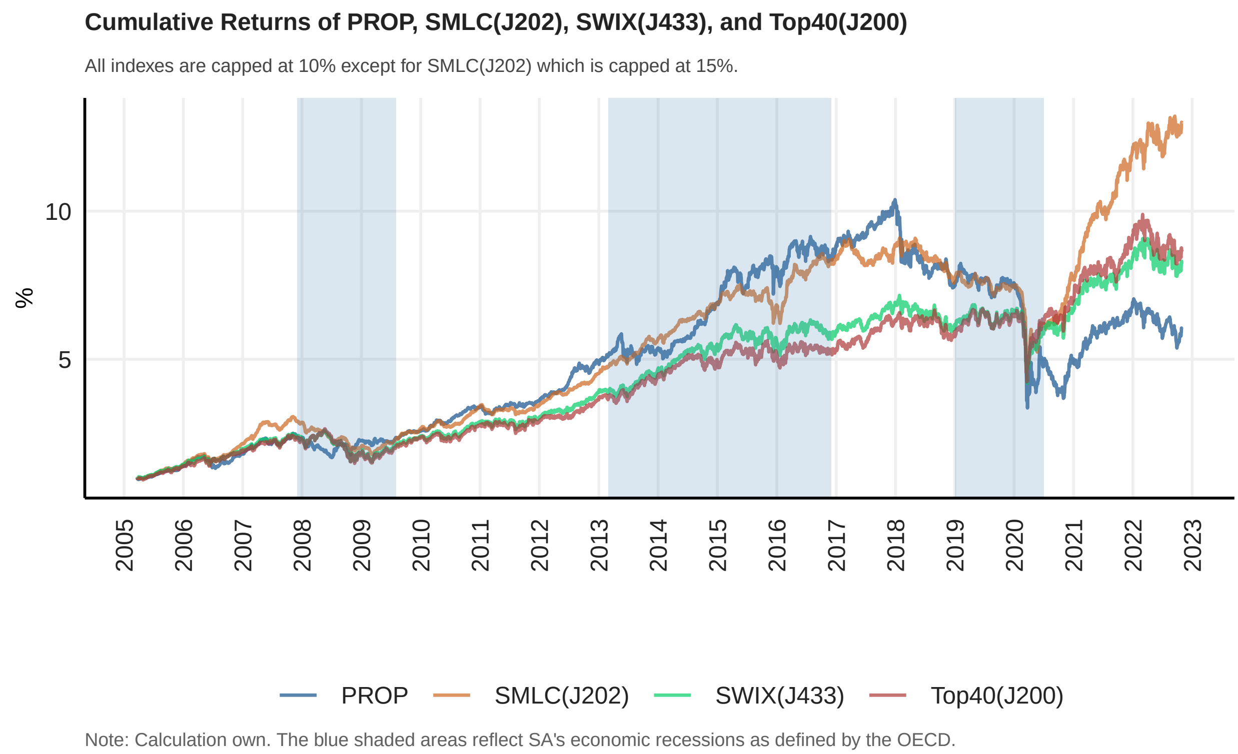


Figure 1.1: Cumulative Returns

The DCC MV-GARCH model's results suggest that, on aggregate, the comovement between PROP, SWIX(J433), and SMLC(J202) is amplified during periods of heightened global economic uncertainty. Although the PROP index is the most volatile of the indexes and the SMLC(J202) index the least volatile, it exhibits a substantially lower time-varying conditional correlation with the SWIX(J433) index compared to the SMLC(J202) index. However, since 2016, this difference has shrunk marginally. On the other hand, the dynamic conditional correlation between the SMLC(J202) and SWIX(J433) indexes is the highest and the more stable among the three index pairs considered. These results infer that an investor holding large proportions of SWIX(J433) constituents will achieve superior portfolio diversification in purchasing listed property compared to SMLC(J202) constituents.

## 2. Results: Inter-Index Comovement and Estimated Volatility

The time-varying dynamic conditional correlations (DCC) are estimated using the estimated univariate GARCH(1,1) models' standardised residuals in the second stage of estimation.

The estimated volatility for each index and time-varying DCC between the PROP, SMLC(J202), and SWIX(J433) indexes are depicted in Figures 2.1 and 2.2, respectively.[4] Figure 2.2 shows that heterogeneity exists between the index pairs over time, indicating that stationary correlation modelling estimates (for example, the Constant Conditional Correlations or CCC) could be deceptive.[5]

Table 2.1 reports the coefficients $a$ and $b$'s estimates and corresponding p-values. From Katzke & others (2013), these estimates signify mean reversion of the time-varying correlations since $a + b < 1$. The impact of lagged standardised shocks on dynamic conditional correlations is measured by the coefficient $a$. In contrast, the measure of the past effect of the dynamic conditional correlations on present dynamic conditional correlations is given by $b$. These parameters are, additionally, statistically significant at the 5% level, except for the $a$ and $b$ coefficients for SMLC(J202), which is significant at the 10% level. Again following Katzke *et al.* (2013), this indicates significant deviations over time, reaffirming that a DCC model is more fitting than a CCC model.

The corresponding estimated DCC model diagnostics, checking for conditional heteroscedasticity through testing for serial correlation, is reported in Table 2.2 below. As stated by Tsay (2013), when the shocks are heavy-tailed, the parameters $Q(m)$ and $Q_k(m)$ often fail to detect the presence of conditional heteroscedasticity, and the $Q_k^r(m)$ robustness parameter is desirable. Consequently, the fitted DCC model fails to reject the null of no autocorrelation when considering the rank-based test and the robustness parameter $Q_k^r(m)$.

The model's estimated volatility for each index (Figure 2.1) shows that PROP is the most volatile in comparison to the SMLC(J202) and SWIX(J433) indexes, especially in the past decade, possessing substantially larger jumps in volatility during recessionary periods (blue shaded areas). Moreover, the SMLC(J202) index is the least volatile.

In analysing the estimated dynamic conditional correlations across index pairs (Figure 2.2), the PROP index exhibits a substantially lower time-varying conditional correlation with the SWIX(J433) index compared to the SMLC(J202) index. However, since 2016, this difference has shrunk marginally. On the other hand, the dynamic conditional correlation between the SMLC(J202) and SWIX(J433) indexes is the highest and the more stable among the three index pairs considered.

[4] Also see Appendix A for the (unmodeled) sample scaled growth and standard deviation in Figures A.1 and A.2, respectively.

[5] I drop the Top40(J200) index due to its similar dynamics to the SWIX(J433) index.

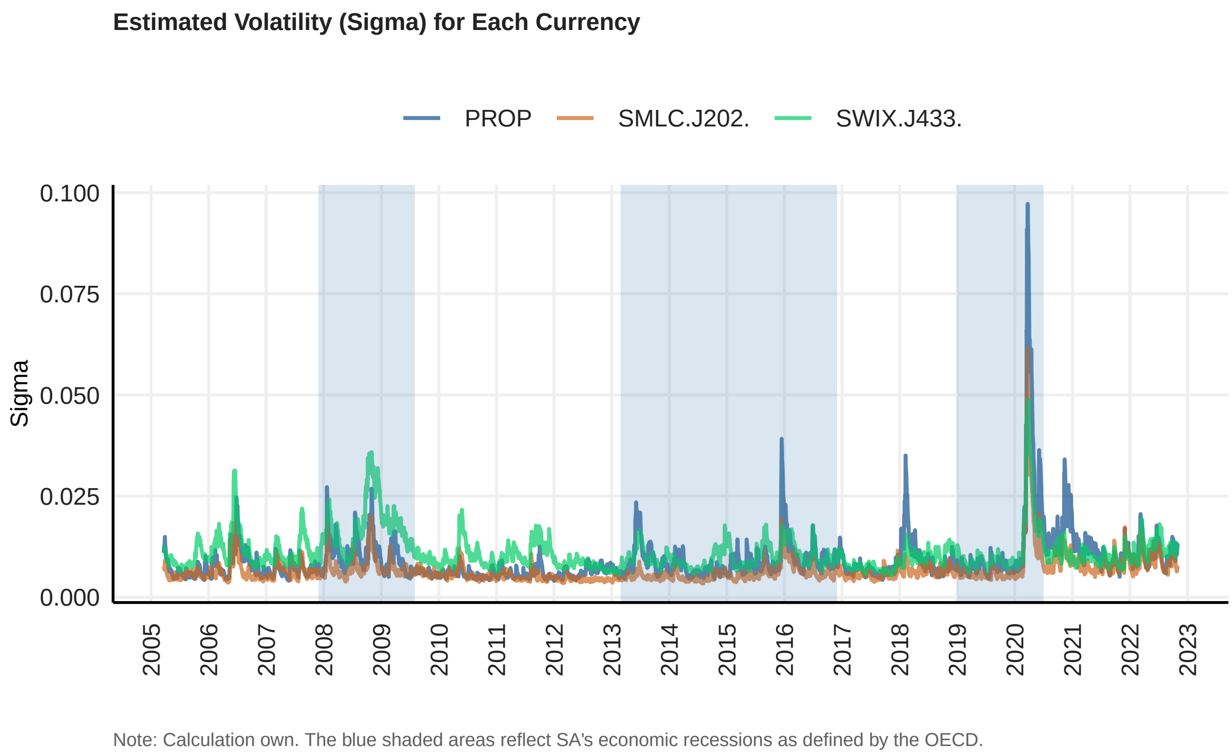


Figure 2.1: DCC GARCH: Estimated Volatility

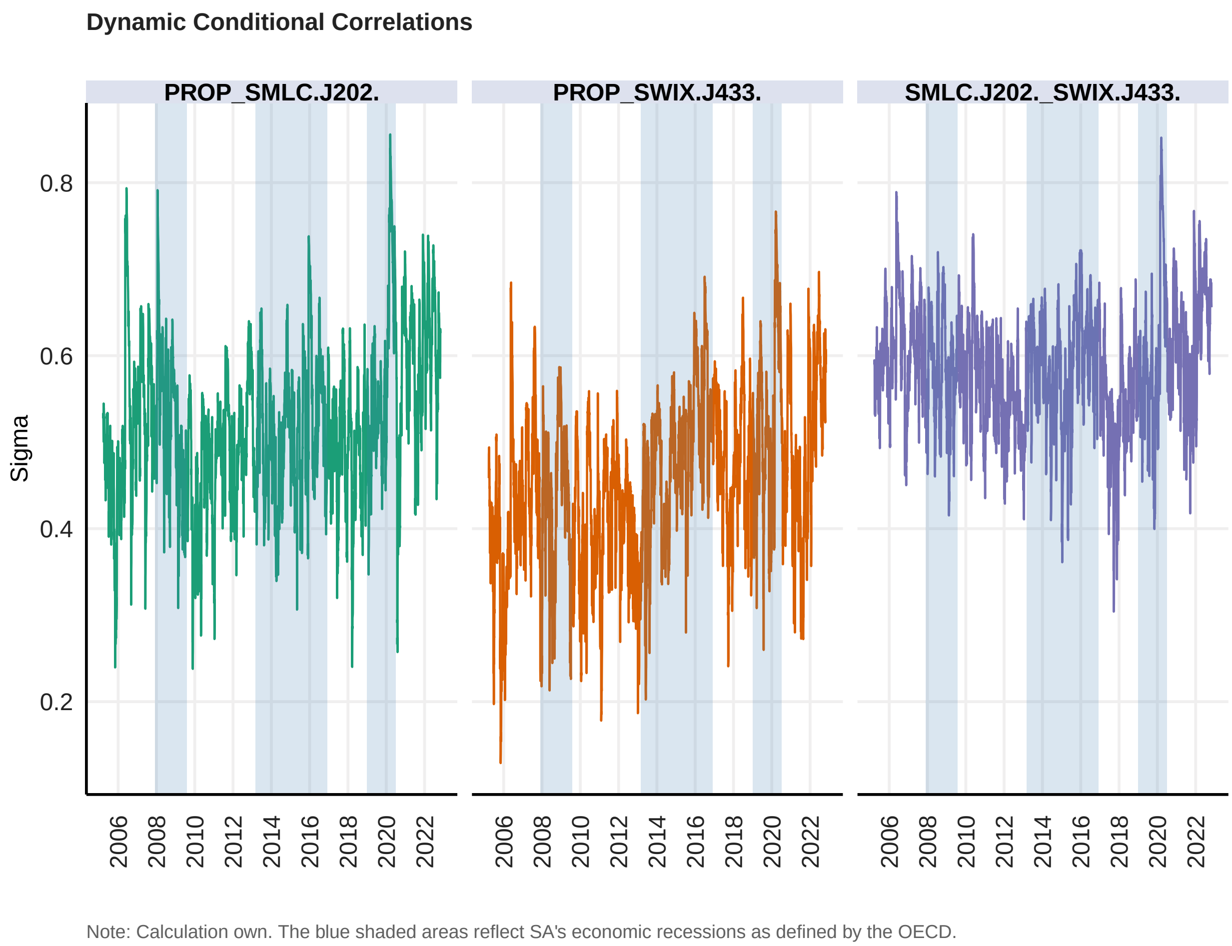


Figure 2.2: DCC GARCH: Dynamic Conditional Correlations

Table 2.1: DCC Model

| | $a$ | $b$ |
|---|---|---|
| SWIX(J433) | 0.147 | 0.841 |
| | (0.0345) | (0) |
| SMLC(J202) | 0.135 | 0.836 |
| | (0.09172) | (0.01) |
| PROP | 0.0996 | 0.8814 |
| | (0.00038) | (0) |
| Note: P-values given in brackets | | |

Table 2.2: Model Diagnostics

| $Q(m)$ | $Rank - based\ test$ | $Q_k(m)$ | $Q_r^k(m)$ |
|---|---|---|---|
| 599.07 | 12.69 | 369.79 | 175.44 |
| (0) | (0.25044) | (0.0784 | (0.19111) |
| Note: P-values given in brackets. | | | |

## 3. Conclusion

The purpose of this project is to investigate time-varying conditional correlations between FTSE/JSE-listed property securities and the broader FTSE/JSE assets by adopting the Dynamic Conditional Correlation (DCC) Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MV GARCH) modelling procedure.

The DCC MV-GARCH model's results suggest that, on aggregate, the comovement between PROP, SWIX(J433), and SMLC(J202) is amplified during periods of heightened global economic uncertainty. Although the PROP index is the most volatile of the indexes and the SMLC(J202) index the least volatile, it exhibits a substantially lower time-varying conditional correlation with the SWIX(J433) index compared to the SMLC(J202) index. However, since 2016, this difference has shrunk marginally. On the other hand, the dynamic conditional correlation between the SMLC(J202) and SWIX(J433) indexes is the highest and the more stable among the three index pairs considered. These results infer that an investor holding large proportions of SWIX(J433) constituents will achieve superior portfolio diversification in purchasing listed property compared to SMLC(J202) constituents.

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## Appendix A.

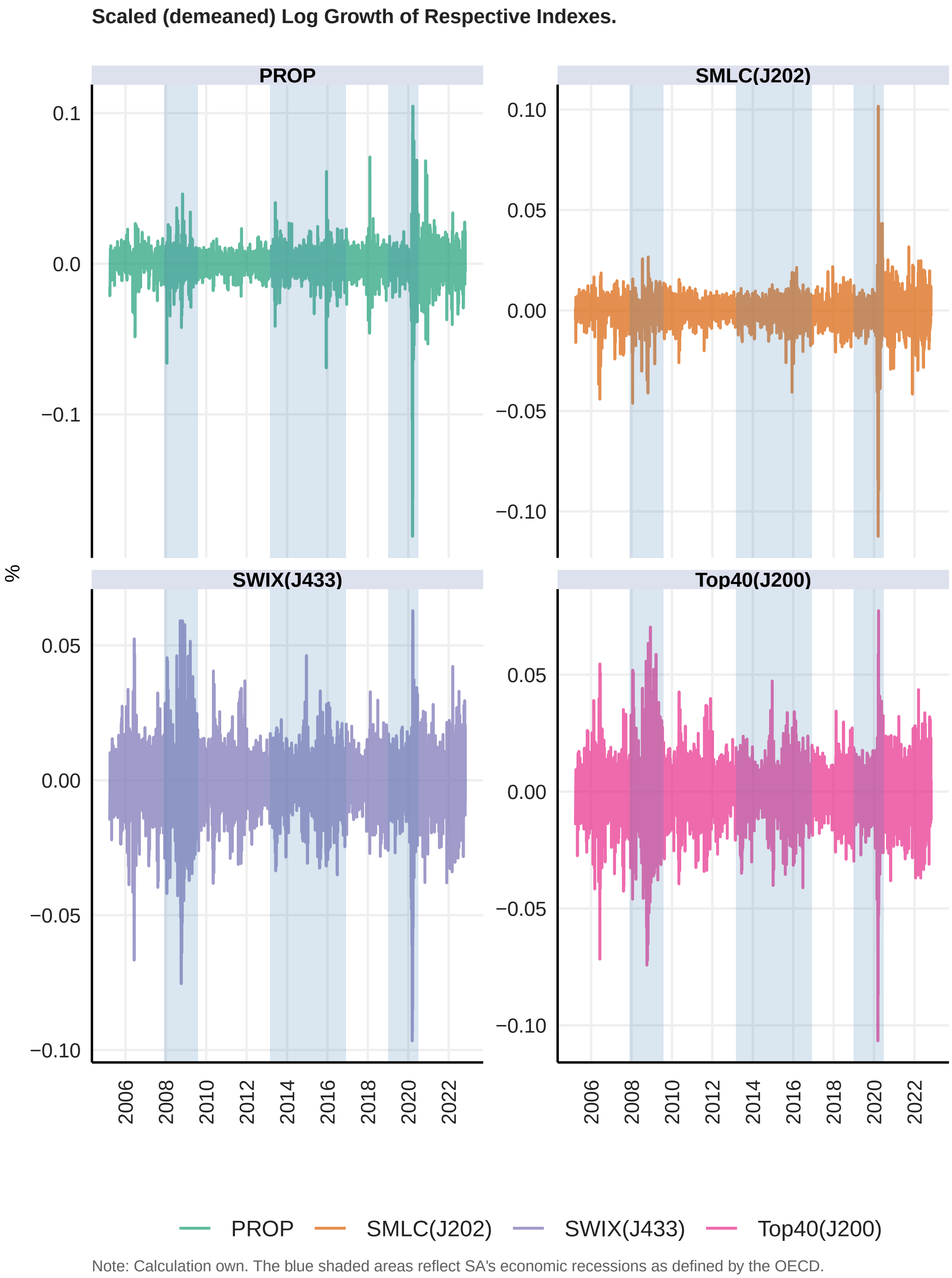


Figure A.1: Scaled Growth

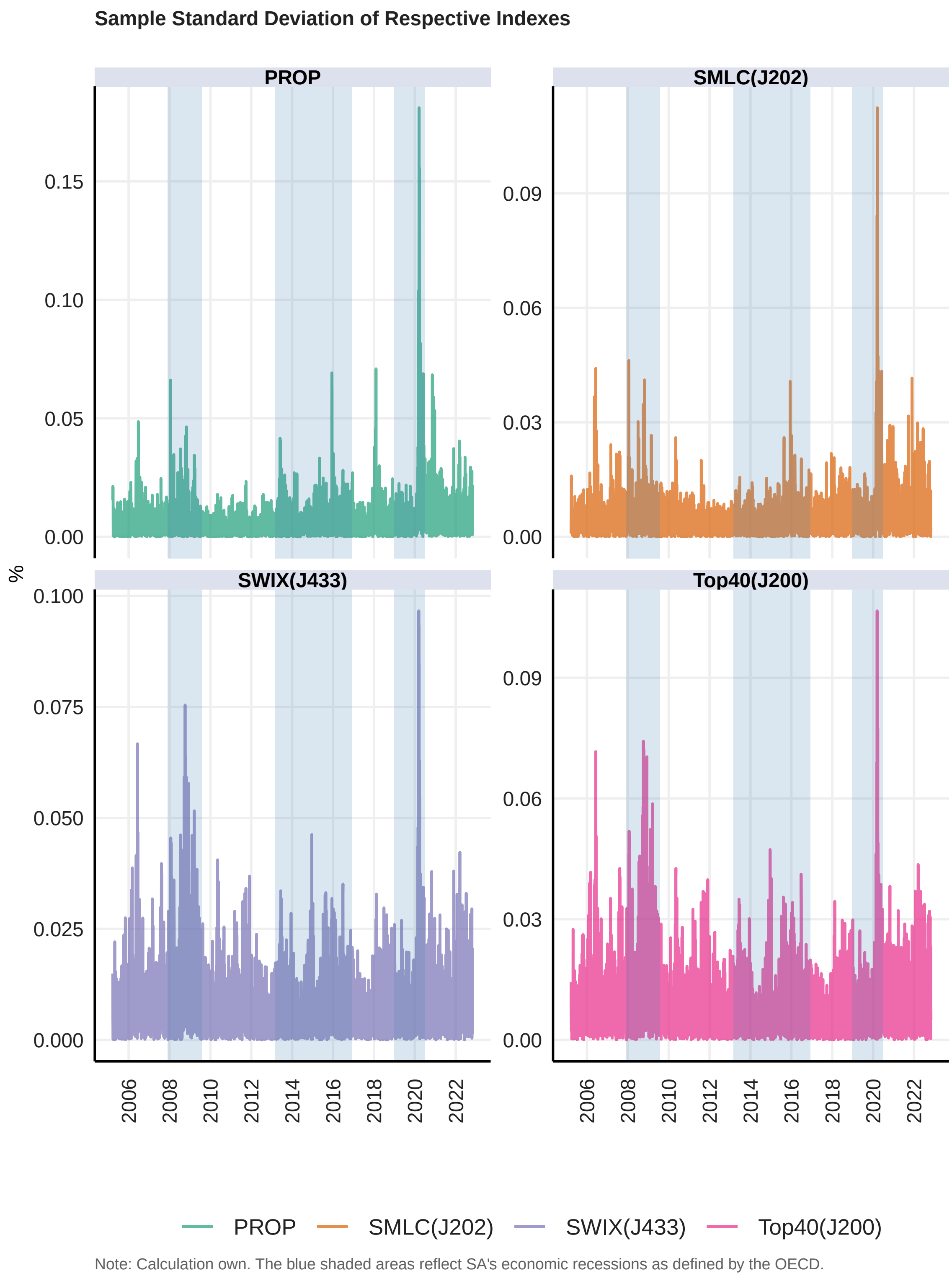


Figure A.2: Sample Standard Deviation