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Interdependence Dynamics of Official and Informal Argentine Exchange Rates through Copulas

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Abstract

We employ copula models to examine the interdependence dynamics between Argentina's official and informal exchange rates, particularly highlighting shifts induced by the COVID-19 pandemic. We observe a pronounced synchronization of market downturns in the aftermath of the pandemic, suggesting an increased susceptibility of the informal market to fluctuations in the official sector. Our findings also highlight policy measures, such as taxation on foreign capital flows, which, though intended to stabilize the market, may inadvertently heighten the risk of exchange rate crises.

Keywords Copula-based models · COVID-19 economic impact · Dependence structure · Exchange rate synchronization

1 Introduction

In the Argentine exchange market, the interdependence between official and informal exchange rates is crucial for understanding the country's broader economic dynamics, particularly in light of its history with currency controls and financial crises. This study explicitly examines this interdependence, where the informal exchange rate, often called the 'blue dollar rate,' is an indicator of Argentina's black market exchange rate. The divergence of this rate from the official rate is influenced by government controls, economic policies, and market sentiment (Calvo & Mishkin, 2003; Edwards, 2002; Mello & Carneiro, 1997). The behavior of exchange rates in Argentina, especially after the switch to a more flexible exchange rate regime in 2015 and the subsequent policy changes, presents a unique case for study (Libman & Palazzo, 2020).

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To address this, we employ copula models, which capture the dependence between random variables by integrating marginal distributions into a joint distribution function. Copulas are advantageous in modeling joint distributions without any distributional assumption (Joe, 1997), a practical feature for capturing exchange rate dynamics. We expand the application of copulas to model the dependence in a multi-exchange system. Our approach includes modeling foreign exchange rates using generalized autoregressive conditional heteroskedasticity (Andersen et al., 2006) to obtain independently and identically distributed residuals (innovations), followed by using bivariate conditional copulas to capture the dependence structure between two exchange rate innovations.

The main advantage of using copulas over traditional methods such as correlation and linear models is their ability to capture the degree of dependence between extreme values (tails), which is necessary for risk management and policy-making in volatile economic conditions. Copulas offer a probabilistic view of capturing tail dependence during extreme market events like crashes or currency crises that significantly impact portfolio performance (Delatte & Lopez, 2013; Turgutlu & Ucer, 2010; Ning, 2010; Reboredo, 2011; Aloui et al., 2013a, b). This study draws on Ardakani (2023a, b) recent contributions to enhance the copula-based framework in capturing the tail dependencies.

The application of copula models has been extensively explored in the literature. For instance, Patton (2006) and Rodriguez (2007) have utilized copula models to examine the dependency between different financial markets and assets, providing evidence on correlation structures during market turmoils. Similarly, Cappiello et al. (2006) have applied copulas to analyze the dynamics of exchange rates in emerging economies, underscoring the models' utility in capturing nonlinear dependencies. Our approach aligns with these methodologies, extending the application to the unique context of Argentina's dual exchange rate system.

Our empirical analysis involves official and informal exchange rates between the U.S. dollar and the Argentine Peso, covering the period from January 1, 2018, to August 30, 2022, with a particular focus on the period before and during the COVID-19 pandemic. Findings highlight a significant evolution in the dependence structure of exchange rates across the pre and post-pandemic periods. The results suggest a distinct change in dependence patterns, characterized by increased synchronization of downturns in the post-pandemic period. This indicates that adverse shocks in the official exchange rate profoundly and directly impact the informal market during the pandemic. The analysis also uncovers that policy measures have paradoxically escalated the risk of an exchange rate crisis.

Considering this interdependence amid the pandemic-induced economic shocks, we illustrate the impacts of policy measures in emerging markets. Echoing the findings of Aghion et al. (2019) on monetary policy effects in emerging economies, our results highlight the balance between stabilization efforts and market volatility. Similarly, Gopinath and Stein (2021) examination of informal markets' roles aligns with our observations on Argentina's multi-exchange rate system, underscoring its significance in buffering external economic pressures and shaping market resilience.

2 Exchange Rate Dependence using Copulas

We utilize copula models for their adeptness in explaining exchange rate dependencies. This methodology allows for the modeling of marginal distributions apart from their interconnections, highlighting copulas' capacity to capture both linear and non-linear correlations, especially under conditions of financial anomalies. This approach is aligned with the literature that underscores the role of tail dependencies in financial markets (Cherubini et al., 2004; Embrechts et al., 2003; Palaro & Hotta, 2006).

We independently model exchange rates and transform them to uniform distributions using the probability integral transform to apply copulas. The copula concept is rooted in the work of Sklar (1959), who demonstrated that any multivariate joint distribution can be decomposed into its marginals and a copula that encapsulates the dependency structure between them. This foundational principle is given by

$$F(x_1, x_2) = C\left(F_1(x_1), F_2(x_2)\right), \tag{1}$$

where C is the copula function, and $F_i(x_i)$ are the marginal cumulative distribution functions (CDFs). This decomposition is useful for financial data like exchange rates, where marginal distributions may not be normally distributed.

We distinguish between elliptical and Archimedean copulas. Elliptical copulas, including the Gaussian and Student-t, are derived from elliptical distributions and are characterized by their symmetry and tail dependence properties (Fischer et al., 2009). The Gaussian copula, for instance, is defined as

$$C_{\mathcal{G}}(u_1, u_2; \rho) = \Phi_\rho(\Phi^{-1}(u_1), \Phi^{-1}(u_2)), \tag{2}$$

where Φ_ρ is the CDF of a bivariate normal distribution with correlation coefficient ρ, and Φ^{-1} is the inverse CDF of a standard normal distribution. Figure 1 illustrates a simulated Gaussian copula. Despite its flexibility, the Gaussian copula lacks tail dependence, making it less suitable for capturing extreme co-movements (Genest & MacKay, 1986).

Conversely, the Student-t copula, capable of modeling tail dependencies (Demarta & McNeil, 2005), is given by

$$C_t(u_1, u_2; \rho, \nu) = T_{\nu,\rho}(T_\nu^{-1}(u_1), T_\nu^{-1}(u_2)), \tag{3}$$

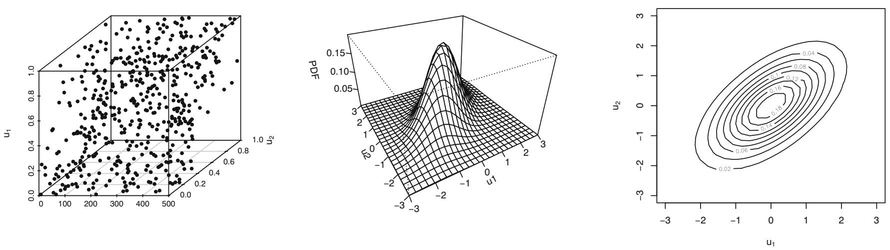

Fig. 1 Scatter, perspective, and contour plots of simulated bivariate Gaussian copula with $\mu = 0, \sigma = 1$ ($n = 500$)

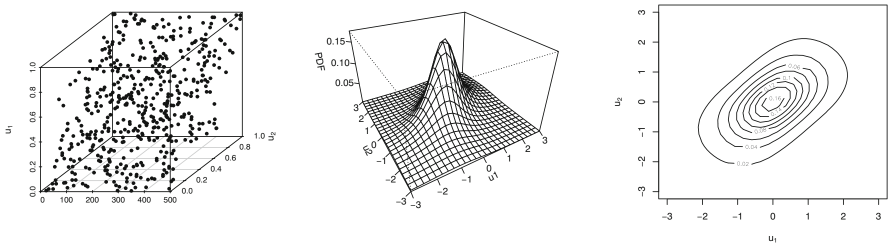

Fig. 2 Simulated bivariate Student-t copula with $\nu = 2$ and $\rho = .6$ ($n = 500$)

where $T_{\nu,\rho}$ is the CDF of a bivariate t-distribution with ν degrees of freedom and correlation ρ, and T_{ν}^{-1} is the inverse CDF of a univariate t-distribution. Figure 2 illustrates a simulated Student-t copula.

Archimedean copulas offer a different approach. Defined through a generator function ψ, such copulas are particularly adept at modeling asymmetric dependencies. The Clayton copula, for example, is expressed as

$$C_{\mathcal{C}}(u_1, u_2; \theta) = \left(\max\{u_1^{-\theta} + u_2^{-\theta} - 1, 0\}\right)^{-1/\theta}, \tag{4}$$

where $\theta > 0$ controls the level of dependency. Figure 3 illustrates a simulated Clayton copula. Archimedean copulas are able to capture a wide range of dependency structures, including scenarios where extreme values in one variable are associated with moderate values in another (Ardakani, 2024).

The Frank copula is an important example among the Archimedean copulas, distinguished by its ability to encapsulate both positive and negative dependencies. The Frank copula is given by

$$C_{\mathcal{F}}(u_1, u_2; \theta) = -\frac{1}{\theta} \ln\left(1 + \frac{(\exp(-\theta u_1) - 1)(\exp(-\theta u_2) - 1)}{\exp(-\theta) - 1}\right), \tag{5}$$

where the dependency parameter $\theta \in \mathbb{R}\backslash\{0\}$ governs the level of association, with positive values indicating a positive dependence and negative values indicating negative dependence between the variables. In Fig. 4, a simulated Frank copula is illustrated. This particular copula is adept at capturing relationships where the occurrence of extreme values in one variable coincides with both extreme and non-extreme values in the counterpart variable, making it a flexible tool in multivariate analysis.

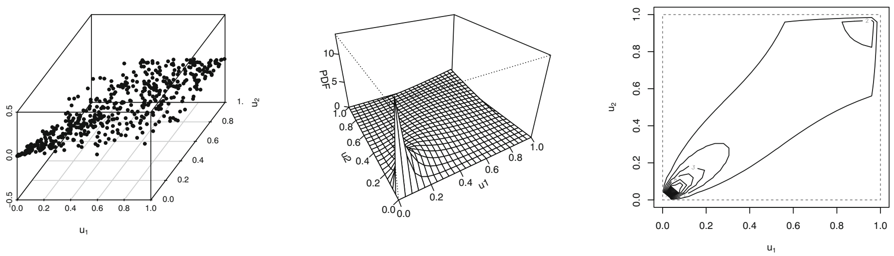

Fig. 3 Simulated bivariate Clayton copula with $\theta = 2$ ($n = 500$)

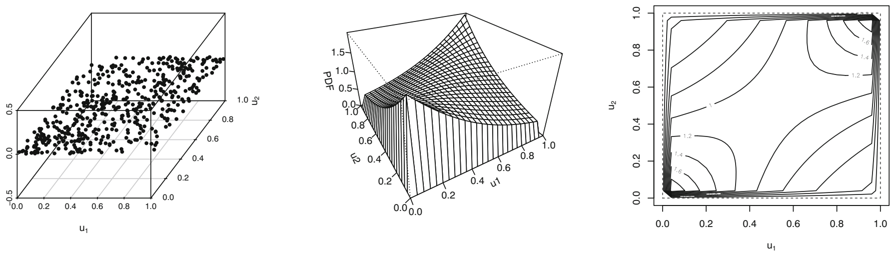

Fig. 4 Simulated bivariate Frank copula with $\theta = 2$ ($n = 500$)

Incorporating these copula classes allows for modeling exchange rate dependencies, particularly in examining the asymmetric dependencies between official and informal rates. Given X_1 and X_2 as the log returns of Argentina's official and informal exchange rates, respectively, and assuming they are coupled through a copula C, the tail dependence coefficients, λ_L for the lower tail and λ_U for the upper tail, can be defined as

$$\lambda_L = \lim_{q \to 0^+} \mathbb{P}(X_2 \leq F_2^{-1}(q) | X_1 \leq F_1^{-1}(q)), \tag{6}$$

$$\lambda_U = \lim_{q \to 1^-} \mathbb{P}(X_2 > F_2^{-1}(q) | X_1 > F_1^{-1}(q)). \tag{7}$$

We hypothesize that λ_L and λ_U exhibit significant deviations from zero during periods of economic turmoil, such as the COVID-19 pandemic, highlighting an increased likelihood of joint extreme value occurrences between the two markets under stressed conditions.

For estimating copula parameters, we use maximum likelihood estimation, optimizing the following log-likelihood function

$$\mathcal{L}(\varphi) = \sum_{t=1}^{T} \ln c(F_1(x_1; \varphi_1), F_2(x_2; \varphi_2); \theta) + \sum_{t=1}^{T} \sum_{i=1}^{2} \ln f_i(x_i; \varphi_i), \tag{8}$$

where the maximum likelihood estimate $\hat{\varphi}$ is given by $\hat{\varphi} = \underset{\varphi}{\operatorname{argmax}}\, \mathcal{L}(\varphi)$.

Patton (2006) extends the notion of copula and employs conditional copula to examine the conditional dependence between the Deutsche mark and the yen. The conditional copula helps model the exchange rates, especially in the presence of covariates and can be estimated by conditional likelihood. See Xu and Lien (2022) and Zhou et al. (2020) for examples in the foreign exchange market. The conditional version of Sklar's theorem provides modeling for the joint distribution of random variable $\mathbf{x}_t = (x_{1,t}, x_{2,t})'$, conditional on information set $\mathcal{F}_{t-1}$ The conditional copula can be defined as

$$F_t(\mathbf{x}|\mathcal{F}_{t-1}) = C_t \left(F_{1,t}(x_1|\mathcal{F}_{t-1}), F_{2,t}(x_2|\mathcal{F}_{t-1}) \right), \tag{9}$$

where C_t is the conditional copula. The information set must be the same for all marginal distributions and the copula; otherwise, $F_t(\mathbf{x}|\mathcal{F}_{t-1})$ is not a valid conditional joint CDF (Patton, 2006). The conditional copula parameters are estimated through a maximum likelihood estimation, where the conditional log-likelihood given by

$$\mathcal{L}(\varphi|\mathcal{F}_{t-1}) = \sum_{t=1}^{T} \ln c(F_1(x_{1,t};\varphi_1|\mathcal{F}_{t-1}), F_2(x_{2,t};\varphi_2|\mathcal{F}_{t-1});\theta|\mathcal{F}_{t-1}) + \sum_{t=1}^{T}\sum_{i=1}^{2} \ln f_i(x_{i,t};\varphi_i|\mathcal{F}_{t-1}). \tag{10}$$

Given the estimated copula parameters, we can employ a non-parametric bootstrap approach to assess the significance of the tail dependence coefficients λ_L and λ_U. We resample the underlying data with replacement B times, re-estimate the copula parameters for each bootstrap sample, and compute the corresponding tail dependence coefficients. The variability observed across the bootstrap samples allows us to construct empirical confidence intervals for λ_L and λ_U. This allows us to evaluate their stability and significance in capturing extreme co-movements between Argentina's official and informal exchange rates. For each bootstrap replicate $b \in \{1, \dots, B\}$:

1. Resample (X_1, X_2) pairs with replacement to create a bootstrap sample $\{(X_1^{*(b)}, X_2^{*(b)})\}$.
2. Re-estimate copula parameters to obtain $\hat{\theta}^{*(b)}$.
3. Compute tail dependence coefficients:

$$\lambda_L^{*(b)} = \lim_{q\to 0^+} \mathbb{P}(X_2^{*(b)} \leq F_2^{-1}(q)|X_1^{*(b)} \leq F_1^{-1}(q)),$$
$$\lambda_U^{*(b)} = \lim_{q\to 1^-} \mathbb{P}(X_2^{*(b)} > F_2^{-1}(q)|X_1^{*(b)} > F_1^{-1}(q)).$$

The empirical distributions of $\lambda_L^{*(b)}$ and $\lambda_U^{*(b)}$ across all B replicates provide a basis for constructing confidence intervals and assessing the significance of the observed tail dependence.

The robustness of copula models in financial data analysis, particularly for exchange rates, is well-documented. See Cherubini et al. (2004) and Embrechts et al. (2003) for examples. The flexibility of copulas in modeling marginal distributions independently from the dependency structure makes them particularly suitable for financial markets characterized by extreme events and tail dependencies (McNeil et al., 2015). Our study draws on the foundational work of Sklar (1959), employing different class of copulas to reflect the varying market conditions pre and post the COVID-19 pandemic. This application echoes the findings of Jondeau and Rockinger (2006), who highlighted the effectiveness of different copula models in capturing the evolution of dependence structures under different market conditions.

Additionally, the examination of exchange rate dynamics in emerging markets has been explored in studies such as Kenourgios et al. (2011) and Mensi et al. (2013), which analyze the impact of economic policies and global events on exchange rates. These studies provide a comparative background to our findings, suggesting broader implications for policy and risk management in similar economic settings. The following section elaborates on applying copula models for Argentina, where various factors, including government policies and global economic events, influence the exchange rate dynamics.

3 Parallel Exchange Rates in Argentina

The parallel exchange rates between the U.S. dollar and the Argentine Peso have resulted from capital controls imposed by the Argentinean government. Most developing countries had pegged exchange rate arrangements in the 1970s, whereas today, they allow exchange rates to float. Under the floating exchange rate regime, the exchange rate is determined by market forces and the central bank's monetary policy. The floating exchange rate regime is extensively studied in the literature (Helpman, 1981; Helpman & Razin, 1982; Reinhart, 2000; Rohit & Dash, 2019; Rose, 2011).

Argentina, however, adopted the currency boards in 1991 to steer inflation (Chang & Velasco, 2000). The currency board is considered an extreme form of a pegged exchange rate to improve the stability of the domestic currency. Under this regime, the foreign country's monetary policy is imported, and the domestic currency is pegged to the foreign rate (Mundell, 1997). The currency board can be problematic when the two countries are experiencing different business cycle phases, and the foreign monetary policy strategy may not work domestically. To avoid this problem, Argentina adopted a floating exchange rate regime after abandoning the currency board in 2002 due to experiencing negative growth.

We study the dependence structure between the official and informal exchange rates from 2018 to 2022. The official exchange rates are obtained from the Central Bank of Argentina, while the informal rates are collected from the financial newspaper Ambito Financiero. The data contains 1,147 daily closing exchange rates from January 1, 2018, to August 30, 2022. We use midpoints of bid-ask quotes as they are generally a less noisy measure of exchange rates. Table 1 provides the summary measures for the daily percent changes of the rates before and after COVID-19. We split the sample when the World Health Organization declared the pandemic a public health emergency on March 11, 2020. The average official and informal values are .15 and .22. Higher informal rates are expected because of the lack of regulation. For both exchange rates, however, the average daily percentage change of exchange rates dropped after the COVID-19 pandemic. The shape of the exchange rate distributions also varies, as shown by the skewness and kurtosis measures.

Table 1 Summary measures of official and informal exchange rates (percent change)

Statistics	Official exchange rate			Informal exchange rate		
	Entire	Pre-COVID	Post-COVID	Entire	Pre-COVID	Post-COVID
Mean	0.15	0.17	0.14	0.22	0.23	0.21
SD	0.86	1.23	0.16	1.68	1.65	1.70
Min	-6.80	-6.80	-0.12	-7.82	-7.50	-7.82
Median	0.08	0.05	0.09	0.00	0.00	0.00
Max	7.35	7.35	1.48	9.36	9.36	9.10
Skewness	1.33	0.89	2.28	0.82	1.22	0.48
Kurtosis	25.58	12.51	13.18	10.04	11.69	8.68

Daily exchange rates from January 1, 2018, to August 30, 2022, are used. The data include midpoints of bid-ask quotes with 1,147 observations

We acknowledge data-related limitations that may influence the interpretation of results. Firstly, the informal exchange rates, while widely recognized, may carry biases distinct from those of the official published rates by the Central Bank of Argentina. This discrepancy potentially affects the comparative analysis between official and informal exchange dynamics. Despite this, the informal rates are widely recognized and used indicators in the market. Their inclusion provides a view of the market beyond the official figures.

Furthermore, our approach utilizes the midpoints of bid-ask quotes to mitigate measurement noise. However, this method may not fully capture the market depth and investor sentiment, as it overlooks the spread between buying and selling prices, which can be a significant indicator of market liquidity and stress, especially in informal markets. This approach is commonly accepted in the literature for its ability to provide a more stable measure of central tendency. It also serves as a reliable proxy for the true market price, especially in the absence of high-frequency data.

Figure 5 plots daily percent changes of the two exchange rates along with their corresponding absolute values. This visualization displays the dynamic change after the pandemic. Volatility clustering is also evident. Volatility clustering refers to the tendency of large changes in exchange rates followed by small changes (Rachev et al., 2011). We capture this volatility clustering using the GARCH models introduced by Andersen et al. (2006) and incorporate the commonly used autoregressive integrated moving average (ARIMA).

We follow a two-step estimation procedure to model the dependence structure of exchange rates through copulas. First, we fit ARIMA-GARCH models to account for the characteristics of each exchange rate and obtain marginal distributions. This approach is suitable for modeling the exchange rates (Andersen et al., 2006) and accommodating time-varying conditional volatility and dependence (Fan & Patton,

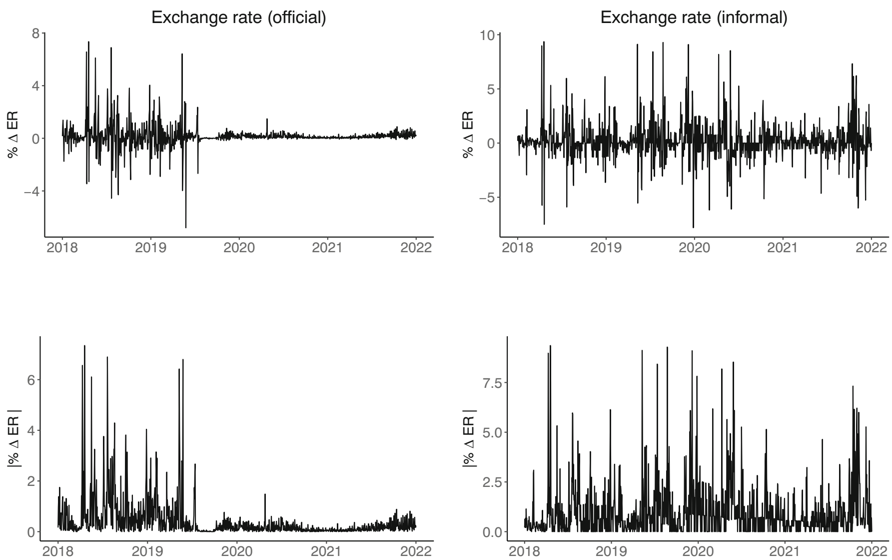

Fig. 5 Daily percent changes and absolute values of official and informal exchange rates

2014). We then model the bivariate innovation distribution by the copula families described in the previous section. The bivariate model specification involves the identification of two marginal distributions and one conditional copula. In summary, the marginal innovation distributions constructed from the ARIMA-GARCH are coupled through a conditional copula.

The ARIMA-GARCH model for the margins can be written as

$$\begin{aligned}
\mathbf{y}_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \mathbf{y}_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \\
\sigma_t^2 &= \delta_0 + \sum_{i=1}^{p} \delta_i \sigma_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 \\
\varepsilon_t &\equiv \sigma_t \nu_t ,
\end{aligned} \tag{11}$$

where $\mathbf{y}_t$ is the daily percent changes of official and informal exchange rates, ν_t is a matrix of strong white noise processes with mean zero and variance one, and α, θ, γ follow the sufficient condition of Nelson and Cao (1992). Also, $\mathbb{V}(\mathbf{y}_t|\mathcal{I}_{t-1}) = \mathbb{V}(\varepsilon_t|\mathcal{I}_{t-1}) \equiv \sigma_t^2$, where $\mathcal{I}_{t-1}$ is the information set at time t defined as the σ-algebra generated by the lagged values of the $\mathbf{y}_t$. The conditional mean from the autoregressive moving average model has the same structure as the conditional variance from the GARCH. We employ quasi-maximum likelihood estimation introduced by Bollerslev and Wooldridge (1992), which assumes a normal distribution and uses robust standard errors for inference.

The ARIMA-GARCH model results are presented in Table 2. The optimal number of lags is selected based on the Akaike Information Criterion (AIC). Different models are specified for the pre and post-COVID periods, and the estimates vary across the subsamples. This finding highlights the importance of modeling the dependence between the two series and helps us understand the change before and after the pandemic. The ARIMA components, represented by α_i indicate the autoregressive nature of the market movements. The statistically significant α_4 in the post-COVID informal exchange rate model suggests a notable autoregressive effect during this period, potentially due to heightened market responses to preceding changes amid pandemic-induced uncertainty. The GARCH components, denoted by δ_i and γ_i, capture the volatility clustering, where high-volatility events tend to cluster together. The notable increase in the γ_1 parameter for the post-COVID informal exchange rate underscores a heightened sensitivity to past squared innovations, indicative of increased market volatility in response to shocks during the pandemic. The discrepancy in χ^2 values across periods and between the official and informal rates reflects the distinct market conditions and the efficacy of the ARIMA-GARCH models in capturing these dynamics. This model provides independently and identically distributed residuals needed for modeling dependence.

After modeling marginal exchange rate distributions, the bivariate conditional copula is applied to the standardized innovations. The conditional distribution of standardized innovations $\nu_t = (\varepsilon_t/\sigma_t)|\mathcal{F}_{t-1}$ is standard normal and serially independent. We consider bivariate kernel density estimation with diagonal bandwidth matrices to visualize the distribution of standardized innovations. The joint densities are obtained

Table 2 Parameter estimates of the ARIMA-GARCH models

	Official exchange rate		Informal exchange rate	
	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID
α_1				0.469
				(0.871)
α_2				-0.110
				(0.191)
α_3				-0.061
				(0.066)
α_4				0.223***
				(0.082)
α_5				-0.033
				(0.192)
θ_1	0.087*	-1.063***	-0.087**	-0.260
	(0.045)	(0.040)	(0.043)	(0.870)
θ_2		-0.021		
		(0.057)		
θ_3		0.133***		
		(0.039)		
δ_0	1.321***	0.004***	2.403***	0.046***
	(0.243)	(0.001)	(0.231)	(0.010)
δ_1	0.199***	0.222***	0.225***	0.068***
	(0.032)	(0.012)	(0.038)	(0.008)
γ_1	0.001	0.765***	0.001***	0.914***
	(0.001)	(0.019)	(0.001)	(0.008)
χ^2	1,714.3	1,843.1	2,367.3	1,269.3

Daily percent changes are used. Robust standard errors are reported in parentheses. Quasi-maximum likelihood estimation of Bollerslev and Wooldridge (1992) is employed, assuming a normal distribution, and uses robust standard errors for inference. Also, α_i are ARIMA model coefficients for autoregressive terms, θ_i are GARCH model coefficients for moving average terms, δ_i are GARCH model coefficients for autoregressive conditional heteroskedasticity terms, and γ_i are coefficients for squared innovations in the GARCH model. χ^2 is the chi-squared statistic for the goodness-of-fit test. *p<0.1; **p<0.05; ***p<0.01

using a bivariate kernel estimator introduced by Duong (2007). The kernel density estimate is defined by

$$\hat{f}(\nu; H) = n^{-1} \sum_{i=1}^{n} K_H(\nu - \nu_i), \tag{12}$$

where ν is the innovation matrix, $\mathbf{H}$ is the bandwidth matrix which is symmetric and positive-definite, $K(\nu)$ is the kernel which is a symmetric PDF, and $K_{\mathbf{H}}(\nu) = |\mathbf{H}|^{-1/2} K(\mathbf{H}^{-1/2}\nu)$. The plug-in selector introduced by Wand and Jones (1993) is used to estimate the joint densities.

Figure 6 presents the contour plots of bivariate kernel density estimates of exchange rate innovations based on the plug-in selectors. The difference in dynamics between the pre and post-pandemic periods is evident. In the pre-COVID plot, the contour lines

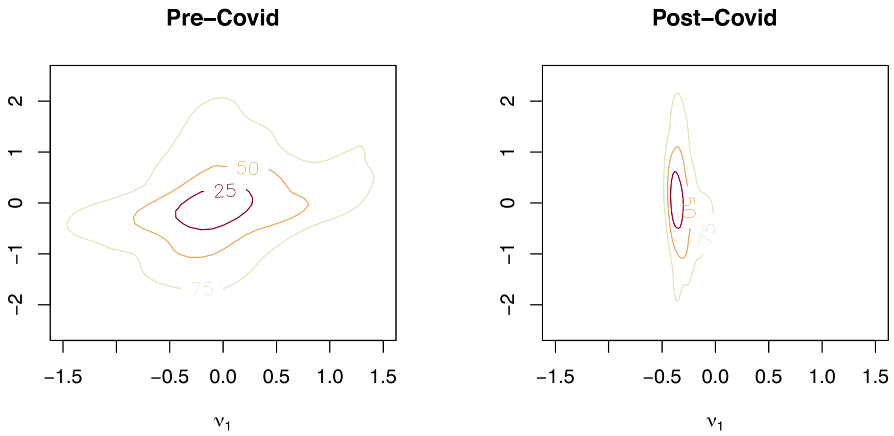

Fig. 6 Bivariate kernel density estimates of exchange rate innovations with plug-in selectors

encapsulate a broader range of values, indicating a more dispersed set of observations in exchange rate fluctuations. The post-COVID visualization, however, exhibits a remarkable contraction in the dispersion, with contour lines tightly huddled around the central axis, suggesting a notable decrease in variability and a more concentrated range of exchange rate innovations. This representation shows the profound impact of the COVID-19 pandemic on currency exchange movements and reflects a significant shift in economic conditions. We can also visualize the dependence between the two standardized innovation series, which changed after the pandemic.

Figure 7 presents implied correlations of exchange rate innovations for both pre-COVID and post-COVID periods. In the pre-COVID era, the correlation starts around a moderate positive level and exhibits a downward trend, ending with a significant drop as the pandemic begins. This suggests that initially, the official and informal markets may have moved in tandem to some extent, but as the pandemic approached, this correlation weakened drastically. Such a trend might indicate diverging market forces or interventions that started to impact the two rates differently. In the post-COVID period, the correlation is noticeably more volatile, with fluctuations ranging from mildly positive to negative values. This instability, in correlation, might reflect the uncertainty and rapid changes in economic conditions caused by the pandemic. Notably, negative correlation spikes suggest instances where the two markets responded inversely to

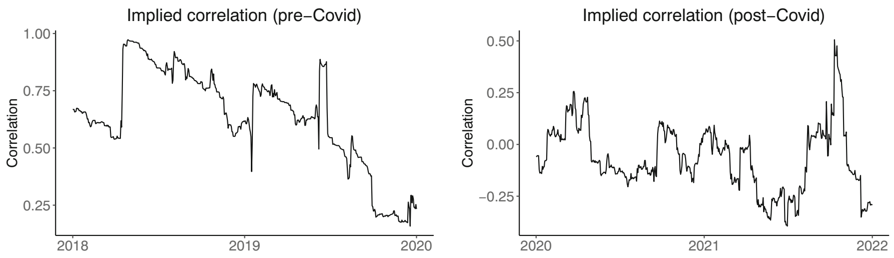

Fig. 7 Implied correlation of exchange rate innovations

certain events or policies. This finding provides insights into the changing dynamics of the exchange rate market in response to macroeconomic shocks and underscores the need for models like GARCH that can capture such volatility and the importance of policy measures that consider the instability of market relationships during times of crisis.

We model the joint distribution of innovations by the conditional copula to capture the dependence between the two standardized innovation series. Exchange rates fluctuate over time, and time-varying conditional copulas would be an appropriate tool for dependence modeling (Andersen et al., 2006; Bauwens et al., 2006). Lee and Long (2009) introduce a copula-based multivariate GARCH model and use it for forecasting foreign exchange rates. We consider a statistical evaluation encompassing both goodness-of-fit tests and AIC/BIC-based model selection criteria. This dual approach ensures that our chosen models provide the best statistical fit to the observed data and capture the tail dependencies characteristic during periods of economic stability and turbulence. We first find the best-fit copula for the exchange rate innovations. We consider AIC and Bayesian Information Criteria (BIC) for copula selection. The copulas are fitted using maximum likelihood estimation, and AIC and BIC are computed for all available copula families. For exchange rate innovations $u_{i,j}, i = 1, \cdots, N,\ j = 1, 2$, the AIC of a bivariate copula family c with parameters $\boldsymbol{\theta}$ is defined as

$$AIC = -2\sum_{i=1}^{N} \ln[c(u_{i,1}, u_{i,2}|\boldsymbol{\theta})] + 2k, \tag{13}$$

where $k = 1$ for one parameter copulas and $k = 2$ for the two-parameter Student-t copula. Similarly, the BIC is given by

$$BIC = -2\sum_{i=1}^{N} \ln[c(u_{i,1}, u_{i,2}|\boldsymbol{\theta})] + \ln(N)k. \tag{14}$$

The penalty for two-parameter families is larger when the BIC is chosen. The copulas are selected based on the AIC and BIC defined in Eqs. 13 and 14. After different copulas are fitted, the copula density with the lowest value is selected. Table 3 presents the estimates of the copula parameters. The copula families are identified, distinguishing between the pre and post-COVID models. The BB7 copula is characterized by both upper and lower tail dependence, indicating that extreme movements in the exchange rates tend to occur together in both tails of the distribution during the pre-COVID era. This is reflected in the positive estimate of Kendall's τ (0.37), implying that the official and informal exchange rates moved together. Conversely, the post-COVID period modeled with the Frank copula exhibits negative Kendall's τ (-0.09), suggesting an inverse relationship between the exchange rates during extreme market conditions. The empirical Kendall's τ closely matches the modeled values, supporting the validity of the copula models. The change in dependence structure could be due to various factors, including increased market volatility, changes in economic policy, or shifts in investor sentiment due to the pandemic. Studies have shown that financial markets can exhibit significant structural changes during periods of crisis. See, for example, Sorensen et al. (2007) and Hartmann et al. (2004).

Table 3 Copula parameter estimates and selection measures for official and informal exchange rates

	Pre-COVID	Post-COVID
Copula models	BB7	Frank
θ_1	1.67	-0.86
θ_2	0.46	–
Kendall's τ (modeled)	0.37	-0.09
Kendall's τ (empirical)	0.36	-0.10
Upper tail dependence	0.48	0
Lower tail dependence	0.22	0
Log-likelihood	114.07	5.39
AIC	-224.14	-8.78
BIC	-215.55	-4.48

The copula model parameters θ_1 and θ_2 correspond to the estimated values that best fit the joint distributions. Kendall's τ provides a measure of the ordinal association between the two exchange rates. Upper and lower tail dependence values indicate the likelihood of extreme movements co-occurring in both markets. Log-likelihood, AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion) assess the model's fit to the data

The economic rationale is also an important factor in selecting the best model beyond statistical evaluation. For the pre-COVID period, characterized by relatively stable market conditions, the BB7 copula is chosen for its ability to capture both upper and lower tail dependencies, reflecting the interconnected movements of official and informal exchange rates under normal economic conditions. Conversely, for the post-COVID period, marked by heightened uncertainty and market volatility, the Frank copula was selected for its capacity to model the divergent behavior observed between the two exchange rates, indicative of the disruptive impact of the pandemic on financial markets.

To empirically validate our choice of copulas, we compared the modeled Kendall's τ values against empirical estimates. The close alignment observed underscores the robustness of our selected models, in line with findings of Nelsen (2006), who highlight the importance of tail dependence in capturing financial market dynamics. Our model selection methods and findings are consistent with methods employed by Rodriguez (2007) in examining financial market dependencies. Furthermore, our results echo the insights of Patton (2006), particularly in understanding the evolving dependence under market stress conditions.

Figure 8 provides the density plots of the estimated copulas for pre and post-COVID periods, illustrating distinct tail behaviors. The post-COVID period exhibits a stronger lower tail dependence, indicating synchronous movements of the official and informal exchange rates towards lower values. This result suggests a stronger concordance in periods of downturns, as evidenced by the pronounced peak in the lower tail of the post-COVID density plot. This finding aligns with the literature that describes how economic crises can lead to enhanced comovements of financial variables, particularly in times of market stress (Hartmann et al., 2004; Xu & Lien,

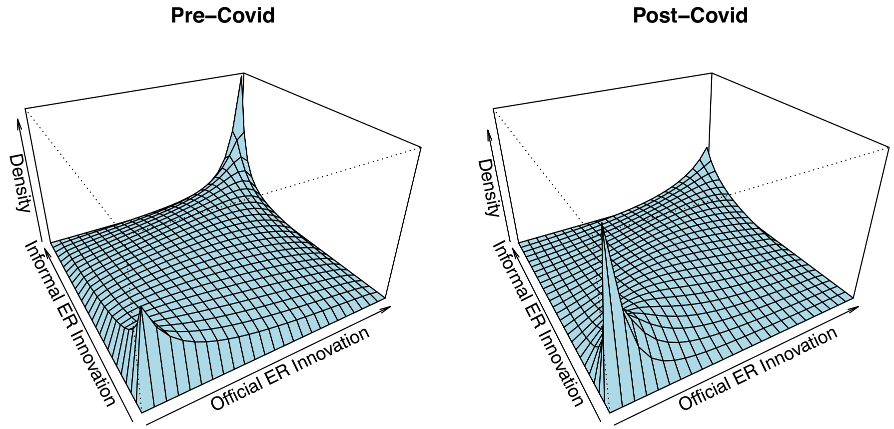

Fig. 8 The density of the estimated copulas for the pre- and post-COVID periods

2022; Zhou et al., 2020). The increased lower tail dependence in the market due to COVID-19 suggests that stress in the official market translates more predictably into informal market movements.This has been documented in studies examining the impact of systemic events on market variables (Sorensen et al., 2007; Glick & Hutchison, 2005). The implications for policymakers are as follows. While the pre-COVID era allowed for some predictability in the response of the informal market to the official market, the post-COVID period suggests that negative shocks in the official exchange rate are more likely to be mirrored in the informal market. This could necessitate a recalibration of policy measures in anticipation of the heightened comovements during market downturns.

The goodness-of-fit results, with a statistic of .05 and a p-value of 0.25, suggest that the selected copula model for the post-COVID data adequately captures the dependence between Argentina's official and informal exchange rates. This aligns with the methodology of empirically validating copula models through comparison with Kendall's τ values, underscoring the model's robustness in reflecting market dynamics. The findings resonate with the literature on financial market dependencies and stress conditions, reinforcing the significance of tail dependencies in understanding market co-movements during crises. The copula parameter estimates and the observed lower tail dependence in the post-COVID period further emphasize the market's vulnerability to negative shocks, highlighting the need for adaptive policy measures to mitigate risks in multi-exchange systems.

4 Concluding Remarks

The uncertainty caused by the pandemic has led to changes in the structure of the foreign exchange markets. This paper studies the dependence structure between Argentina's official and informal exchange rates and provides information on financial market behaviors under varying economic conditions. Results suggest that the dependence structure of exchange rates is subject to significant shifts, as evidenced by the differing patterns observed in the pre and post-COVID periods. The pre-COVID positive dependence indicated a predictable response of the informal market to the official market. In contrast, the increased lower tail dependence observed in the post-COVID period underscores a heightened synchronization in downturns, implying that negative shocks in the official exchange rate market are more likely to have a mirrored impact in the informal market. The findings illustrate how copulas can be utilized to examine dependency dynamics, especially during extreme market events.

Shifts in the dynamics between Argentina's official and informal exchange rates under the stress of the pandemic suggest potential implications for policymakers and market participants to anticipate and mitigate the impacts of future economic shocks. For instance, the observed synchronization in downturns during the post-pandemic period highlights the need for more responsive policy measures to manage exchange rate volatility and protect against cascading market effects. Our use of copulas to model these dependencies offers a methodological framework for analyzing similar phenomena in other contexts, providing insights for both economic theory and practical financial market regulation.

The findings highlight several areas for future research. In evaluating the efficacy of monetary and fiscal policies in mitigating global economic disturbances in emerging economies, future studies could employ copula models to study the interactions among different financial markets. Specifically, methods developed by Ardakani (2024) provide a robust framework for modeling economic dependencies using advanced copula techniques, offering a foundation for such studies. These methods establish a link between copula entropy and mutual information and propose a lower bound for copula entropy. Furthermore, Ardakani et al. (2024) apply a microeconometric method to capture the dynamics of financial markets under stress, which could be utilized in understanding the impact of policy interventions in volatile market conditions.

The utilization of information theory and divergence measures in Ardakani and Saenz (2022) to capture economic inequality, along with the findings of this study, provide a framework that can be extended to analyze the divergence in exchange markets. This methodology can also be expanded to investigate how digital currencies and fintech innovations might influence market dynamics and contribute to or mitigate economic disparities. Further, comparative studies across emerging economies with dual exchange rate mechanisms could reveal divergences in how these economies respond to external shocks, providing insights for policymakers. Moreover, the integration of high-frequency data, motivated by the computational tools in Ardakani and Saenz (2023), can enhance the precision of these analyses. This approach would allow researchers to capture the immediate effects of economic policies and global events on exchange rate discrepancies.

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