ON THE ASYMMETRIC AND DE-ANCHORED IMPACTS OF EXCHANGE RATE ON INFLATION RATE IN EGYPT: A NON-LINEAR MIDAS EVIDENCE

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Abstract

This paper employs a mixed data sampling approach to analyse the potential impacts of daily exchange rate on monthly inflation rate. Our results indicate that the response of CPI inflation to changes in the NEER is asymmetric. While exchange rate depreciation results in a persistent increase in the inflation rate, the inflation-reducing effect of the exchange rate appreciation is minimal and limited to small changes. Meanwhile, the information content of daily exchange rate for explaining inflation outcomes varies significantly over the month. We, therefore, estimate a mixed-frequency model that accounts for the intra-month dynamics of exchange rate to predict next-month inflation on a daily basis. Our estimated indicator of daily inflation reveals that inflation expectations have recently showed signs of de-anchoring. Over 2020, expectations were more responsive to forecast revisions, actual inflation, and cross-expectations spill-overs.

الملخص

تستخدم هذه الدراسة منهج البيانات ذات التكرارات المختلطة لتحليل التأثيرات المحتملة لسعر الصرف اليومي على معدل التضخم الشهري. تشير نتائج النموذج إلى عدم تكافؤ استجابة معدل تضخم الرقم القياسي لأسعار المستهلكين للتغيرات في سعر الصرف الاسمي الفعال؛ فبينما يؤدي تراجع قيمة العملة المحلية إلى ارتفاع دائم في معدل التضخم، يقتصر انخفاض معدل التضخم الناتج عن تحسن قيمة العملة المحلية على مدى صغير وفقط عند زيادة قيمة الجنيه المصري بشكل محدود. في ذات الوقت، يتسم المحتوى المعلوماتي لسعر الصرف اليومي بالتباين الملموس في تفسير نتائج معدل التضخم على مدار الشهر. لذلك، قمنا بتقدير نموذج ذو تكرارات مختلطة يأخذ في الاعتبار ديناميكيات سعر الصرف خلال الشهر للتنبؤ بمعدل التضخم الشهري القادم على أساس يومي. وفقًا للمؤشر اليومي لمعدل التضخم الشهري المٌقدر، أظهرت توقعات التضخم في الآونة الأخيرة علامات عدم إرساء واضحة. خلال عام ٢٠٢٠، استجابت توقعات التضخم طويلة المدى بشكل أكبر لمراجعات توقعات الخبراء، ومستجدات التضخم الفعلي، وتوقعات التضخم قصيرة الأجل.

1. Introduction

Forecasting inflation in real time has been particularly challenging with the recent floatation of the foreign exchange market in Egypt. The huge depreciation in the value of Egyptian pound that followed the Central Bank of Egypt's (CBE) decision in November 2016 has not only left inflation rate higher but also more volatile. In this uncertain environment, both consumers and businesses still need to make early predictions about future inflation in order to adjust prices and wages. The monetary authority must also update its projections on the future trajectory of inflation rate to conduct monetary policy in a timely manner. A central bank monitoring vigilantly the evolution of inflation rate can hardly wait until the next release is published. In Egypt, inflation figures come even with a further lag of two business weeks. Policymakers, rather, ought to know as early as possible whether, how, and by how much certain policy announcements and/or macroeconomic news will affect the expected inflation. The monetary authority shall be then able to closely assess the credibility of its inflation target and so take an ex-ante expectations anchoring position. Only if expectations are well-anchored, central banks can maintain price stability, as it prevents transitory shocks of inflation from feeding into long-term mechanisms of price and wage formation, see for example Bernanke (2007) and Draghi (2014).

The objective of the current research is, therefore, the estimation of an early indicator of the inflation rate that can be used to monitor inflation expectations and consequently (de)-anchoring status on a daily basis. To that end, I investigate the information content of the daily exchange rates for predicting the monthly inflation rate in real time. Put differently, I estimate what inflation rate would look like if there were a daily inflation release based on the new information from the foreign exchange market. If daily innovations of exchange rate can explain the monthly realizations of inflation or if, vice versa, inflation outcomes affect exchange rate path, then the latter should be useful in predicting inflation on a daily basis. Recent contributions on Egypt show that the exchange rate Granger-causing inflation (Khodeir (2012) and Awad (2019)), is a superior monetary policy transmission channel than interest rate (Hosny (2013) and Lemaire (2018)), and has a larger pass-through effect on consumer relative to producer prices (Massoud (2014) and Helmy et al. (2018)).

The statistical modelling of this relationship is, still, problematic because of the frequency mismatch between the low-frequency inflation rate and the high-frequency exchange rate. A straightforward solution to this problem is the use of mixed-frequency regression models. Following Ghysels et al. (2020), I employ MIxed DAta Sampling (MIDAS) regression models for estimating monthly realizations of inflation rate with daily innovations of exchange rate for the period from 2003M01 to 2020M08. Our results confirm that the information content of daily Nominal Effective Exchange Rate (NEER) is not negligible and significantly improves the explanation of monthly outcomes of Consumer Price Index (CPI) inflation. The impact of the daily changes in the NEER on the monthly CPI rate is, as expected, highly significant and negatively signed. The MIDAS analysis indicates that important information can be lost if one absolutely ignores the high-frequency NEER dynamics. The Likelihood Ratio (LR) test rejects the average- against the MIDAS model at 5% significance level, that is not only aggregate but also intra-month components of exchange rate determine inflation rate.

Furthermore, the use of non-linear and semi-parametric MIDAS models reveal substantial non-linearities for the impact of daily exchange rate on monthly inflation rate. First of all, the responses of CPI inflation rate to the changes in the NEER, increases and decreases, are asymmetric in terms of magnitude and timing. Although the depreciation effect of the NEER index causes a persistent increase in the CPI rate, the inflation-reducing effect of the exchange rate appreciation is limited to a small range, beyond which the impact is further reversed. Secondly, adding the short-term interest rate as a second low-frequency regressor reveals a threshold non-linearity in the behaviour of monthly CPI inflation rate. A moderate inflation-reducing impact appears only when the interest rate is sufficiently high, that is beyond 12% in our application. This small deflationary effect of the interest rate, therewith, represents an improvement in relation to the muted impact of the early empirical evidence. Thirdly, the daily innovations of exchange rate do not always exert the same influence over the month on the inflation rate. The data-driven impact of the individual NEER components varies smoothly with the size of its total amount and the relative effect of above-average exchange rate observations is penalized. Overall, these results remain qualitatively similar if the NEER is, for example, replaced by the USD/EGP bilateral exchange rate.

Following Ghysels and Wright (2009), the estimated MIDAS models are then employed to generate daily indicators of the inflation rate. The daily indicators predict how the inflation rate would respond to latest information from the currency market should there be a certain shock that day. In this case, MIDAS models should be helpful for assessing the unobservable inflation within the month, that is on non-release dates. The resulting MIDAS-based daily inflation indicator is therefore compared with more direct methods of forecasting inflation within the month. Nevertheless, it is not obvious how to evaluate the proposed indicators of daily inflation since inflation realizations remain unobservable on non-release days. I here follow Monteforte and Moretti (2013) and compare the proposed daily indicators of inflation with the next inflation release. Unfortunately, this criterion is not without problems in our exercise as it presupposes that the final modification of the monthly inflation rate has already appeared immediately after the preceding release. Each time inflation rate changes at some later day within the month, this underestimates the informational content of our indicator by enlarging forecast errors. Despite this problem, our results suggest that our MIDAS-based indicator is more useful for forecasting inflation within the month than other indicators that completely ignore the high-frequency dynamics of the exchange rate.

We then make use of our estimated daily indicator by investigating the degree of inflation expectations (de-)anchoring in Egypt. Our analysis indicates that inflation expectations are generally well-anchored except for the period of exchange rate floatation around late 2016. Inflation expectations have, however, showed signs of de-anchoring over 2020 to present. Inflation expectations have become more responsive to regular revisions in expert forecasts about macroeconomic variables including exchange rate; they also became more sensitive to developments in actual lagged inflation rate; while longer term inflation expectations have become more dependent on inflation expectations of shorter horizons.

The rest of our paper is organized as follows. Section 2 revisits the existing literature and describes our dataset. Section 3 introduces the baseline MIDAS model. Section 4 dissects the estimation results and discusses the daily inflation indicator. Section 5 provides evidence on the anchoring of inflation expectations. Section 6 offers some concluding remarks.

2. Exploring Inflation Dynamics through the Lens of Exchange Rate

Economic theory postulates that the relationship between inflation rate and exchange rate is dual. On the one hand, the purchasing power parity hypothesis, absolute or relative, argues that changes in the nominal exchange rate should offset movements in relative prices until domestic purchasing power in a two given countries is equal. A surge of domestic inflation in one country should, ergo, be compensated by a decline in the value of its own currency to keep the relative prices constant, see for example Taylor and Taylor (2004). On the other hand, literature distinguishes between two channels through which changes in exchange rate can be transmitted to domestic inflation: a direct channel that conveys exchange rate shocks to domestic prices through adjusting import prices of production inputs and final products and an indirect channel that relates the impacts of exchange rate movements to the export prices of locally produced inputs and final goods. Still, the overall pass-through effect depends on the degree of economic openness and the exchange rate regime adopted, see for instance Campa and Goldberg (2005) and Choudhri and Hakura (2006).

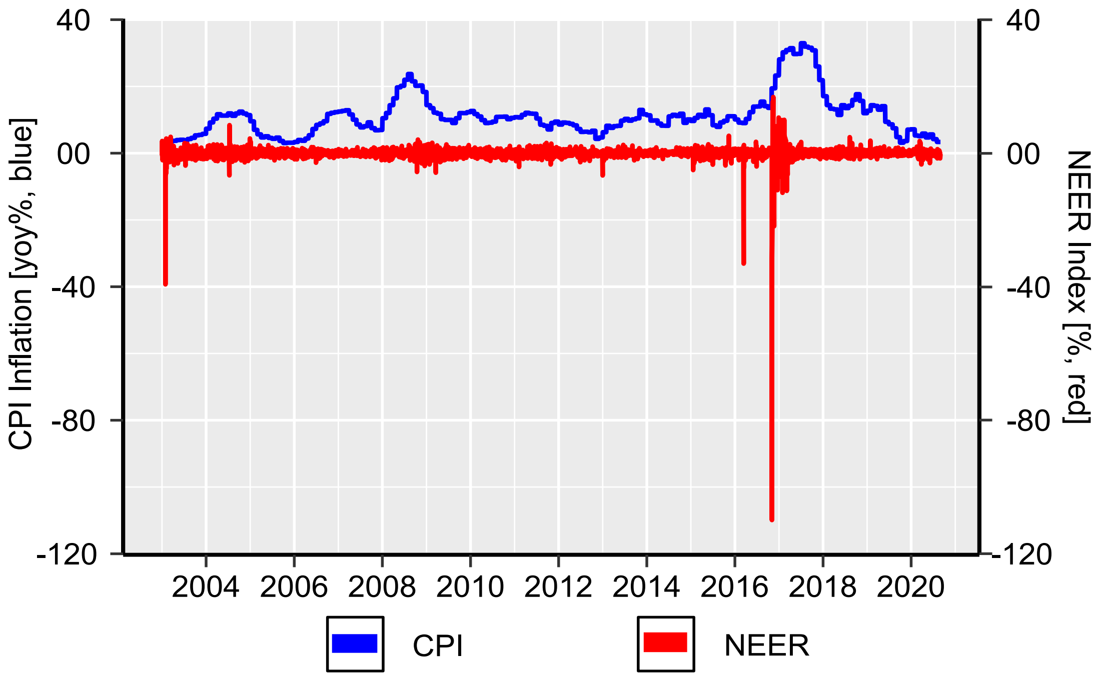
As a small and comparatively open economy that has recently moved to a managed float regime after anchoring its currency to the US dollar for decades, the link between exchange rate and inflation rate has been rather unique in Egypt. Khodeir (2012) showed that the bilateral exchange rate of EGP against the USD Granger causes changes in the inflation rate. Relative to interest rate, exchange rate has proved to be a key channel for monetary policy transmission, particularly when it was used as a nominal anchor, see for example Hassan (2003), Billmeier and Al-Mashat (2007), Hachicha and Lee (2009), Abdel-Baki (2010), Hosny (2013), and Lemaire (2018). A larger pass-through effect of exchange rate to consumer prices than to producer prices is documented by Massoud (2014) and Helmy et al. (2018). Awad (2011) and Awad (2019) have also proved that the exchange rate pass-through effect is time varying. Early evidence has, still, paid little attention for a three aspects in modelling the exchange rate impact on inflation rate. Namely, the potential non-linearities in the inflation rate empirics, the usefulness of daily exchange rate innovations for understanding inflation dynamics, and the anchoring power of exchange rate on inflation rate.

2.1. Inflation Rate Non-Linearities and Exchange Rate Empirics

Early literature on Egypt has often assumed a linear relationship between exchange rate and inflation rate. Yet, this assumption is quite strict based on the findings of empirical research on comparable countries. By developing a theoretical model, Taylor (2000) establishes that the impact of exchange rate on inflation rate relies on the initial level and the persistence of inflation rate. He finds out that the lower and more persistent the inflation rate is, the smaller the degree to which firms pass-through exchange rate changes to their selling prices. Ball and Mankiw (1995) also showed that relative prices are more responsive to large shocks than to small shocks when adjustment costs are high. The impact of exchange rate on inflation rate could, accordingly, be disproportionate based on the extent of the currency shock. The pass-through effect of exchange rate on inflation could as well depend on the direction of the shock, appreciation or depreciation, see for instance Steel and King (2004). In managed exchange rate regimes, firms may rapidly adjust their prices in reaction to depreciation shocks expecting they are permanent while, if the exchange rate appreciates, they may be reluctant to change their prices anticipating that they have a transitory impact on their costs.

Figure 1 shows that the association between the NEER index and the CPI inflation is fairly strong in Egypt. The correlation rate between the two variables equals -42% in the period from 2003M01 to 2020M08. This correlation, however, jumped to -71% after the floatation of the domestic currency late 2016. The same pattern can also be observed for the mean of the inflation rate which increased from 10% to 15% after the pound floatation. It is evident that the exchange rate floatation has not only lift inflation rate to double-digits but also made it more volatile. The standard deviation of the inflation rate has more than doubled in the subsequent period of the floatation decision. That being the case, it is not surprising that the log changes in the NEER index often lead to a subsequent (de)-inflationary wave in the CPI inflation. What is still not obvious and marks our first contribution is to investigate the potential asymmetric impacts of the currency positive and negative shocks on inflation rate. Compare, for example, the surge in inflation following the first devaluation in 2003 with the inflation decline after introducing the interbank foreign exchange market in 2004.

Figure 1. CPI Inflation and NEER Index for Egypt [%]
(2003M01-2020M08)



Notes: CPI is the monthly seasonally non-adjusted inflation rate of total items while NEER is the log changes in daily trade-weighted nominal effective exchange rate with 2010 as a base year. The NEER index is constructed such that an increase means appreciation whereas the decrease reads depreciation. Despite mixed frequencies, both series span the time interval from 2003M01 to 2020M08.
Source: Thomson Reuters Database with codes "EYCPCCPIF" and "JPEGEEN" for CPI inflation rate and NEER index, respectively. Data was last updated on 15 September 2020.

2.2. Uncovering Inflation Dynamics Using Daily Exchange Rate

Since June 2005, the CBE has taken serious steps to develop its monetary policy framework with the objective of implementing an Inflation Targeting (IT) regime over the medium term, see Mashat and Billmeier (2008). The transition to this regime is mainly justified by the repercussions of using exchange rate as a nominal anchor in the past decades. Exchange rate fluctuations even under the proposed regime has a major weight. The floatation decision of 2016 is only a necessary but not sufficient condition toward the successful application of the IT regime, see for instance Berganza and Broto (2012). The increased exchange rate volatility and the vulnerabilities of the financial system may expatiate the already high pass-through effect of exchange rate on inflation rate, see for example Edwards (2006).

Real-time monitoring of developments in consumer prices resulting from daily changes in exchange rate is hence crucial for the CBE to efficiently conduct monetary policy. Expected depreciation of the pound as conveyed by uncovered interest rate parity or exchange rate misalignments may reflect market expectations about future inflation. Empirical literature on the link between high-frequency dynamics of exchange rate and inflation rate empirics is surprisingly scant, due to data availability for instance. Exploring the information content of the intra-month movements of exchange rate for explaining the monthly inflation rate declares, therefore, our second contribution in this paper. Andreou et al. (2013) adequately elucidate the benefits of using daily financial data to forecast and nowcast future values of less frequent macroeconomic variables. For inflation in particular, Monteforte and Moretti (2013) and Marsilli (2017) prove that the inclusion of daily financial indicators in a mixed frequency set-up improves inflation forecasts compared to models that only consider same low-frequency variables in the Euro Area and the United States, respectively.

The MIDAS model, put forward by Ghysels et al. (2002), is therefore specifically suitable for short-term macroeconomic forecasting using high-frequency market leading indicators. The mixed-frequency models have been widely used in the recent literature for nowcasting volatility of financial markets (Emre Alper et al. (2012) and Santos and Ziegelmann (2014)), explaining and predicting output growth (Clements and Galvão (2009) and Marcellino and Schumacher (2010)), real-time forecasting of the governmental budget (Ghysels and Ozkan (2015) and Damane (2020)), predicting the number of tourist arrivals (Bangwayo-Skeete and Skeete (2015) and Önder et al. (2019)), understanding the dynamics of oil pricing (Pan et al. (2017) and Zhang and Wang (2019)), improving prediction accuracy of inflation rate (Li et al. (2015) and Breitung and Roling (2015)), and even forecasting survey and market forecasts of inflation rate (Ghysels and Wright (2009) and Hanoma and Nautz (2019)). The key finding of this brand of literature is that the use of financial information significantly improves the explanation and prediction of the low-frequent macroeconomic variables. The reason behind this improvement according to Nautz (2012) is because of the better representation of the structural determinants of the low-frequency regressands.

2.3. The Anchoring Power of Exchange Rate on Inflation Rate

Exchange rate is an important macroeconomic instrument that could help in ensuring low and stable levels of inflation. Still, the high pass-through effect of exchange rate on inflation rate is a concern for the CBE, which considers adopting an IT regime over the medium term. Anchoring exchange rate fluctuations might gradually dominates inflation targeting in the to be established regime. The challenge now is how to smoothly navigate between "flexible inflation targeting" and "discipling exchange rate volatility", see Youssef (2007). Keeping the exchange rate pass-through effect low could help in reducing the actual inflation rate, which in turn supports stabilizing the impact of exchange rate on inflation rate, see Taylor (2000). To do so, the monetary authority has to demonstrate in practice that it can guarantee lasting price stability by regularly monitoring and anchoring inflation expectations to the announced target. A one major source of potential inflation expectations de-anchoring is the transitory shocks of exchange rate. Analysing the degree of inflation expectations (de)-anchoring in Egypt labels, thence, the third contribution of our paper.

It seems that the CBE has already gained some credibility related to price stability after the announcement of its first inflation target zone of (13% $\pm$ 3%) in May 2017. It is true that the average long-term inflation expectations, say the four-years ahead inflation forecast from the Economist Intelligence Unit (EIU), was not even close to the lower bound of the target zone, but the announcement has definitely helped to reduce the sensitivity of long-term inflation forecasts to short-term news and announcements, including those related to exchange rate. Professional forecasters have only once revised their long-term inflation expectations in the year after announcing the inflation target. The second forecast revision was introduced two months before the modification of the inflation target zone to (9% $\pm$ 3%) in December 2018. This time the average of the four-years ahead inflation forecast was well above the lower bound of the new target corridor in the subsequent year. In 2020, long-term inflation forecasts were not only regularly revised (7 times in twelve months) but also their average was far below the lower bound of the target zone (less than 5%). If expectations are not firmly anchored, there is limited scope to focus on anything else but inflation.

3. The MIDAS Bridge Between Exchange Rate and Inflation Rate

The natural framework for investigating the information content of daily exchange rate for monthly inflation rate is MIDAS models. MIDAS regressions solve the frequency mismatch problem between the low-frequency regressand and high-frequency regressor(s). Instead of restricting the analysis to monthly aggregates, say averages, exchange rate measures are modelled at their daily frequency. The use of MIDAS regression ensures extracting the best fitting alignment of low- and high-frequency data. As a result, potential information losses and mis-specification errors can be avoided, see for instance Andreou et al. (2011). As a starting point, consider the stylized MIDAS regression in Equation 1:

$$\pi_t = \mu + \sum_{r=1}^{q} \alpha_r \, \pi_{t-r} + g\left(\sum_{i=0}^{k} w_i \bigtriangleup log\; E_{s(t)-i}; \beta\right) + \varepsilon_t, \;\; s.t \qquad (1)$$

$$\forall\, i,\; w_i = h(\gamma, i) = \frac{\psi(\gamma, i)}{\sum_{j=0}^{k} \psi(\gamma, j)} \;\; and \;\; \sum_{i=0}^{k} w_i = 1$$

In the baseline specification of MIDAS, monthly inflation rate is projected onto percentage changes in daily exchange rate augmented with lagged inflation rate. Where the seasonally non-adjusted monthly inflation rate of total items is denoted by π_t $(t = 1, ..., 212)$, while $\bigtriangleup log\; E_\tau$ $(\tau = 1, ..., 4664)$ is the percentage change in daily trade-weighted nominal effective exchange rate, and m_t is the number of business days per month t which is equal in our case for all months $\forall\, t, m_t = m = 22$ and so $s(t) = m * t = 4664$. The index τ indicates the total number of business days available up till and including the t^{th} low-frequency observation as given by $\tau = s(t) = \sum_{j=1}^{t} m_j$. We restrict the estimation period in our application to the stable period from 2003M01 to 2020M08. The float of the Egyptian Pound in November 2016 is not a complete regime change, in our view, as the exchange rate was regularly adjusted via a crawling peg with the US dollar between 2003 and 2016 and was, therefore, fairly flexible. This choice is confirmed by the results of standard unit root tests in Appendix A1. The lags of low- and high-frequency variables are chosen by the BIC information criterion as of q = 2 for the monthly inflation and k = 44 for the daily NEER. This wide lags window ensures a better modelling of non-linearities in the CPI inflation empirics, if any.

The inclusion of this big number of daily lags in an unrestricted model would rapidly eat up the model's degrees of freedom. To circumvent this problem, MIDAS models assume that the impact of daily percentage changes in exchange rate $\triangle\ log\ E_\tau$ on monthly inflation rate π_t is determined by functional constraint h which aligns low- and high-frequency variables. The shape of functional constraint h, in return, is governed by the order of lag $i \in 0, \ldots, k$ and a small set of hyper-parameters γ. At the end, the choice of the underlying function ψ is what determines the admissible shape(s) of h. In practice, one can apply any parametric function given that it achieves parsimony and flexibility of γ while retaining that $\sum_{j=0}^{k} \psi(\gamma, i) \neq 0$. Empirically, the hyper-parameters vector of γ is estimated from the sample data and, thus, the constraint is flexible up to the permissible shapes by function h. Since the high-frequency lags are weighted according to h, the lag estimates are then restricted to an equal value, the low-dimensional slope β. The normalization condition $\sum_{i=0}^{k} w_i = 1$ is often required for the identification of β and/or g. When parametric, β shall be the low-dimension slope of the g function. If non-parametric, the condition $\beta \equiv 1$ will be imposed on g.

3.1. Quasi-Linear MIDAS Models (QL-MIDAS)

When g is affine, with $\{\triangle\ log\ E_{s(t)-i}\}_{i=0}^{k}$ linear in variables and $\epsilon_t \sim i.i.d.(0, \sigma_\epsilon^2)$, this results in the Quasi-Linear MIDAS (QL-MIDAS) model as per Equation 2. For this model, the beta weighting function is the most widely employed in applied work, see for example Ghysels et al. (2002), Ghysels et al. (2007), and Bai et al. (2013). Having two hyper-parameters (d = 2), the beta polynomial is highly parsimonious with $\psi(\gamma, i) = x_i^{\gamma_1 - 1}(1 - x_i)^{\gamma_2 - 1}$, where $x_i = \xi + (1 - \xi)\frac{i-1}{k-1}$ given that $\xi > 0$ is marginally small quantity. Ghysels and Qian (2019) further impose $\gamma_1 \equiv 1$ which still yields a flexible constraint with a single parameter to be estimated, γ_2. Restricting $\gamma_1 = \gamma_2 \equiv 1$ leads to the average (equally-weighted) model.

$$\pi_t = \mu + \sum_{r=1}^{2} \alpha_r\, \pi_{t-r} + \beta_1 \sum_{i=0}^{43} h(\gamma, i) \triangle\ log\ E_{s(t)-i} + \varepsilon_t,\ \ s.t \tag{2}$$
$$\forall\ i,\ h(\gamma, i) = \frac{x_i^{\gamma_1 - 1}(1 - x_i)^{\gamma_2 - 1}}{\sum_{j=0}^{k} x_j^{\gamma_1 - 1}(1 - x_j)^{\gamma_2 - 1}};\ x_i = \xi + (1 - \xi)\frac{i - 1}{k - 1}\ with\ \xi > 0\ and\ \sum_{i=0}^{43} w_i = 1$$

The previous model becomes non-linear in parameters, but not in variables, whenever the beta function is applied. The Non-linear Least Squares (NLS) is, thus, used for its estimation via numerical optimization as it has no explicit solution as per Equation 3.

$$\hat{\theta} = \underset{(\mu,\alpha_1,\alpha_2,\beta_1,\gamma')'}{\text{argmax}} \sum_t \left(\pi_t - \mu - \alpha_1 \pi_{t-1} - \alpha_2 \pi_{t-2} - \beta_1 \sum_{i=0}^{43} h(\gamma, i) \triangle \, log \; E_{s(t)-i} \right)^2 \tag{3}$$

3.2. Non-Linear Parametric MIDAS Models (NP-MIDAS)

In these models, the parametric form of both regression function g and functional constraint h is assumed to be known and non-linear, while the underlying parameter vectors β and γ are to be estimated. Similar to the QL-MIDAS, the functional constraints on parameters of the non-linear MIDAS are explicitly imposed assuming that $\sum_{i=0}^{k} h(\gamma, i) = 1$. The Logistic Smooth Transition MIDAS (LSTR-MIDAS) proposed by Galvão (2013) is a perfect example of the NP-MIDAS models. Equation 4 shows that β_2 would be only significant if the non-linearity further induced by the LSTR-MIDAS improves upon the QL-MIDAS model. [1] As per Equation 5, the LSTR-MIDAS introduces non-linearity by permitting the impact of the exchange rate components to smoothly vary with the size of the exchange rate total quantity. This is obvious since the total exchange rate-related quantity $\sum_{i=0}^{k} h(\gamma, i) \triangle \, log \; E_{s(t)-1}$ is in the numerator of the non-linearity-inducing logistic function. The non-negativity condition of $\beta_3 > 0$ in Equation 5 is imposed for identification while the normalization of β_3 through the division by σ_x is only necessary when multiple regressors are considered.

$$g_t(\theta) = \mu + \sum_{r=1}^{2} \alpha_r \pi_{t-r} + \beta_1 \sum_{i=0}^{43} h(\gamma, i) \triangle log E_{s(t)-i} \left[1 + \beta_2 \mathcal{G} \left(\sum_{i=0}^{43} h(\gamma, i) \triangle log E_{s(t)-1}; \beta_3, \beta_4 \right) \right], \tag{4}$$

$$\text{where } \mathcal{G}\,(..) = \left[1 + \exp \left(-\beta_3 \frac{\sum_{i=0}^{43} h(\gamma, i) \triangle log E_{s(t)-1} - \beta_4}{\sigma_x} \right) \right]^{-1} \in [0, 1] \tag{5}$$

where $\theta = (\mu, \alpha_1, \alpha_2, \beta_1, \beta_2, \beta_3, \beta_4, \gamma')'$ and $\mathcal{G}$ the non-linearity-inducing logistic function.

[1] Please note that direct testing of ($H_0 : \beta_2 = 0$) against ($H_1 : \beta_2 \neq 0$) is problematic because β_3 and β_4 cannot be simply identified under the null hypothesis of linearity ($H_0 : \beta_2 = 0$).

The non-linearity in the MIDAS with Min–Mean–Max Effects (MMM-MIDAS), unlike the LSTR-MIDAS, emerges from the individual impact of each observation among all the daily observations of exchange rate $\{\triangle \ log \ E_{s(t)-i}\}_{i=0}^{k}$ and not from their joint effect. The MMM-MIDAS allows for the influence of single observations to be non-linearly up- or downgraded depending on their size relative to the moving average as well as the value and sign of β_2. For instance, the impact of individual components of the exchange rate will be magnified if this particular observation is higher than the moving average and $\beta_2 > 0$. The significance of the non-linearity implied by the MMM-MIDAS can be, hence, directly tested using $(H_0 : \beta_2 = 0)$ against $(H_1 : \beta_2 \neq 0)$. As before, the MMM-MIDAS can be obtained by explicitly replacing the standard functional restriction h by $\widetilde{h}$ as per Equation 6.

$$g_t(\theta) = \mu + \sum_{r=1}^{2} \alpha_r \pi_{t-r} + \beta_1 \sum_{i=0}^{43} \widetilde{h} \left(\{\triangle \ log \ E_{s(t)-i}\}_{i=0}^{k}; \beta_2, \gamma, i \right) \triangle \ log \ E_{s(t)-i}, \quad \text{where} \tag{6}$$

$$\sum_{i=0}^{43} \widetilde{h}(..) \triangle \ log \ E_{s(t)-i} = \begin{cases} (k+1) w_{i_{\max}} \max(\triangle \ log \ E_{s(t)}, ..., \triangle \ log \ E_{s(t)-k}), & \beta_2 = \infty \\ \sum_{i=0}^{k} h(\gamma, i) \triangle \ log \ E_{s(t)-i}, & \beta_2 = 0 \\ (k+1) w_{i_{\min}} \min(\triangle \ log \ E_{s(t)}, ..., \triangle \ log \ E_{s(t)-k}), & \beta_2 = -\infty \end{cases} \tag{7}$$

For brevity, weight indices are $i_{max} = \underset{i \in \{0,...,k\}}{\text{argmax}} \triangle \ log \ E_{s(t)-i}$, $i_{min} = \underset{i \in \{0,...,k\}}{\text{argmin}} \triangle \ log \ E_{s(t)-i}$, $w_i := h(\gamma, i)$, $\widetilde{h}(..)$ is the non-linearity-inducing function, and $\theta = (\mu, \alpha_1, \alpha_2, \beta_1, \beta_2, \gamma')'$.

3.3. Semi-Parametric MIDAS Models (SP-MIDAS)

It extends the standard parametric model with some non-parametric function. Two models are here considered: Partially Linear Effects MIDAS (PL-MIDAS) and Single Index MIDAS (SI-MIDAS). In the PL-MIDAS, the quasi-linear term is augmented with a non-parametric function $g(.)$ in terms of vector z_t which can include further low-frequency variables such as the interest rate, a few of the exchange rate components, or their aggregates like the median. In my application, I use the monthly weighted average of deposit rates for less than 3 months as an additional low-frequency regressor. Notice that the PL-MIDAS model in Equation 8 does not include a constant as it simply would not be identified.

$$\pi_t = \sum_{r=1}^{2} \alpha_r \, \pi_{t-r} + \beta_1 \sum_i h(\gamma, i) \bigtriangleup log \, E_{s(t)-1} + g(z_t) + \varepsilon_t \tag{8}$$

Likewise, the SI-MIDAS model in Equation 9 can be derived from the QL-MIDAS model by eliminating the parametric term connected with function g, for example by setting $\beta \equiv 1$. The impact of the daily exchange rate is, therefore, not associated with any parameter β_1 as before so that to identify the regression function g. The functional constraint on parameters is then imposed assuming that $\sum_{i=0}^{k} h(\gamma, i) = 1$, as usual. For further methodological details about the estimation of semi-parametric MIDAS regressions, revise for instance Breitung and Roling (2015), Ghysels et al. (2016) and Ghysels et al. (2020).

$$\pi_t = \sum_{r=1}^{2} \alpha_r \, \pi_{t-r} + g \left(\sum_{i=0}^{43} h(\gamma, i) \bigtriangleup log \, E_{s(t)-1} \right) + \varepsilon_t \tag{9}$$

4. Is Daily Exchange Rate Informative for Monthly Inflation Rate?

In this section, the MIDAS framework is employed to investigate the information content of daily exchange rate for the monthly inflation rate. In a first step, we estimate the unrestricted quasi-linear MIDAS model (QL^U) that builds on the beta polynomial. The results presented in the first column of Table 1 demonstrate a significant and negative impact of the percentage changes in the daily exchange rate on the monthly inflation rate. The relevant estimate of the low-dimensional slope $\hat{\beta}_1^{\mathrm{QL^U}}$ is highly significant and plausibly signed for the NEER index. Ceteris paribus, a decline in the NEER index value leads to an increase in the CPI inflation. This finding is consistent with existing evidence on the monetary policy transmission mechanisms in Egypt, see for example Mashat and Billmeier (2008), Hosny (2013), Helmy et al. (2018), where they conclude that the exchange rate pass-through effect to CPI inflation rate is substantial, at least, in the short run. The low-dimensional slope $\hat{\beta}_1^{\mathrm{QL^R}}$ of the restricted MIDAS model (QL^R) suggests that even the NEER monthly averages have some information content for the CPI inflation rate, as per the second column of Table 1.

Table 1. The Information Content of the Daily Exchange Rate for the Monthly Inflation Rate

$$\pi_t = \mu + \sum_{r=1}^{2} \alpha_r \, \pi_{t-r} + g \left(\sum_{i=0}^{43} \, w_i \triangle \, log \; E_{s(t)-i}; \beta \right) + \varepsilon_t, \;\; s.t$$
$$\forall \; i, \; w_i = h(\gamma, \; i) = \frac{\psi(\gamma, \; i)}{\sum_{j=0}^{k} \psi(\gamma, \; j)} \;\; and \;\; \sum_{i=0}^{43} \, w_i = 1$$

	MIDAS Model Specification					
	QL^U	QL^R	LSTR	MMM	PL	SI
$\hat{\mu}$	0.00^{**}	0.01^{**}	0.00	0.01^{**}		
	(0.00)	(0.00)	(0.00)	(0.00)		
$\hat{\alpha}_1$	1.33^{***}	1.33^{***}	1.41^{***}	1.34^{***}	1.24^{***}	1.29^{***}
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
$\hat{\alpha}_2$	-0.38^{***}	-0.38^{***}	-0.44^{***}	-0.38^{***}	-0.27^{***}	-0.32^{***}
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
$\hat{\gamma}_1$	3.70^{***}		6.80^{***}	32.41^{***}	3.57^{**}	6.90^{***}
	(1.04)		(0.50)	(0.00)	(1.46)	(0.29)
$\hat{\gamma}_2$	2.67^{***}		6.79^{***}	25.14^{***}	2.14^{***}	3.28^{***}
	(0.56)		(0.32)	(0.00)	(0.67)	(0.23)
$\hat{\beta}_1$	-2.78^{***}	-2.03^{***}	-1.48^{***}	-2.67^{***}	-3.41^{***}	
	(0.37)	(0.69)	(0.31)	(0.00)	(0.66)	
$\hat{\beta}_2$			9.56^{***}	-2.37^{***}		
			(0.06)	(0.00)		
$\hat{\beta}_3$			35.04^{***}			
			(0.01)			
$\hat{\beta}_4$			0.00^{***}			
			(0.00)			
$\hat{\text{bw}}$					0.92^{**}	0.00^{***}
					(0.38)	(0.00)
LR	0.03^{**}					
R^2	0.94	0.94	0.95	0.94	0.95	0.94
N	211	211	211	211	210	211
σ^2	0.01	0.02	0.01	0.01	0.01	0.01

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: π_t denotes the monthly seasonally non-adjusted inflation rate of total items while the percentage changes in daily trade-weighted nominal effective exchange rate is indicated by $\triangle \; log \; E_{s(t)-i}$. Despite different frequencies, both series span the same time interval from 2003M01 to 2020M08. Table (1) presents the estimation results for five specifications of the MIDAS model. Respectively, (QL^U) and (QL^R) represent the unrestricted and the restricted versions of the Quasi-Linear MIDAS model (QL-MIDAS) shown in Equation 2, LSTR- and MMM-MIDAS are two variants of the Non-Linear Parametric models (NP-MIDAS) in Equations 4 and 6, and PL- and SI-MIDAS are two shapes of the Semi-Parametric MIDAS models (SP-MIDAS) as per Equations 8 and 9. Standard errors are shown in parentheses. LR displays the p-value for the Likelihood Ratio test of the restricted (QL^R) vs. the unrestricted (QL^U) Quasi-Linear MIDAS model. bw is the local smoothing estimator of the Semi-Parametric MIDAS models.

The MIDAS analysis, however, reveals information losses if one completely ignores the high-frequency dynamics of daily NEER. In fact, the Likelihood Ratio (LR) test rejects the degenerate model (QL^R) against the unrestricted model (QL^U) at 5 percent significance level. Given that result, it is not unexpected that the hyper-parameter estimates ($\hat{\gamma}_1$ and $\hat{\gamma}_2$) of the QL-MIDAS are highly significant at 1 percent significance level. The information content of daily exchange rate does impact the outcomes of monthly inflation in a sophisticated way that considers the high-frequency dynamics and not just the aggregates of the NEER index. This result upholds the early findings of Ghysels and Wright (2009) and Hanoma and Nautz (2019) about the formation of short- and long-term professional inflation expectations using interest rate differentials and market-based expectations, respectively.

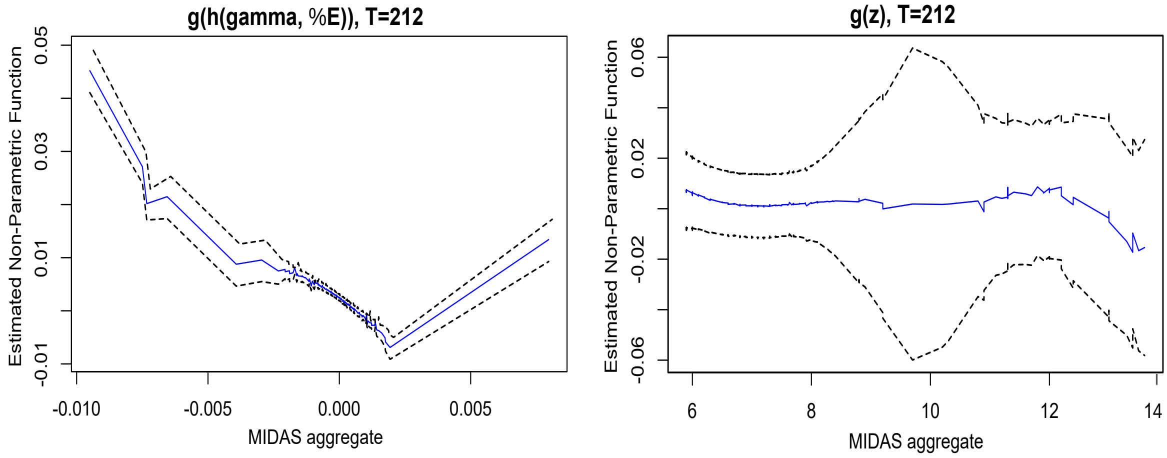
4.1. Uncovering Non-Linearities in the CPI Inflation Empirics

Having established the significance of the QL-MIDAS model, as $\hat{\beta}_1^{\mathrm{QL_U}} \neq 0$ holds, we now investigate potential non-linearities in the CPI inflation dynamics, if any. [2] The results of the non-linear parametric MIDAS models reveal substantial non-linearities in the behaviour of monthly CPI inflation with respect to the daily changes in the NEER index. In the LSTR-MIDAS, the significance of $\hat{\beta}_2^{\mathrm{LSTR}}$ in the third column of Table 1 confirms that the influence of the daily components of exchange rate changes smoothly with the size of the total NEER index-related quantity. The non-linearity in the CPI inflation empirics does not only relate to the aggregate impact of exchange rate but also with the relative effect of its daily innovations. In particular, the negative sign of the highly significant slope coefficient $\hat{\beta}_2^{\mathrm{MMM}}$ in the fourth column of Table 1 establishes that the relative influence of the higher than average observations is penalized. These non-linearities, however, seem to have only a minor effect on the predictive precision of the non-linear over the quasi-linear models. The estimated R^2 of the LSTR-MIDAS model increases only slightly from 94% to 95% relative to the QL-MIDAS while it remained unchanged for the MMM-MIDAS model.

[2] Notice that the non-linearity-inducing functions, represented by parameters β_2 to β_4 in the LSTR-MIDAS or by parameter β_2 in the MMM-MIDAS, would be only identified whenever the low-dimensional slope of the QL-MIDAS β_1 is significant, see Equations 4 and 6.

Figure 2. The Estimated Non-Parametric Functions for the Semi-Parametric MIDAS Models

(a) Single Index MIDAS (b) MIDAS with Partially Linear Effects



Notes: The non-parametrically estimated functions $g_z(z_t)$ and $g_z(\gamma; \triangle \log E_{t,k})$ along with their variability bounds of 95% for the PL-MIDAS and the SI-MIDAS models, respectively.

It is not only the magnitude of the exchange rate changes that matter, as per the results of the MMM-MIDAS model, but also the direction of that change, according to the findings of the SI-MIDAS model. The estimated non-parametric function along with its 95% variability bounds of the SI-MIDAS displays an asymmetric impact of the positive/negative changes in the daily exchange rate on the monthly inflation rate. The responses of consumer prices to the increasing/decreasing effects of the NEER are not the same in terms of direction and strength. While the depreciating effect of the NEER leads to an increasing and persistent surge in the CPI inflation, the inflation-reducing impact of the exchange rate appreciation is weak and only restricted to a small range, beyond which the influence is further reversed. Our dual evidence on the disproportionate impact of the exchange rate on the inflation rate in terms of direction and magnitude is in line with the findings of well-established literature. Ball and Mankiw (1995) seminal contribution on how firms, when price adjustment is costly, disproportionately respond to large but not to small shocks may explain the excessive impact of the above-average NEER index movements on the inflation rate. The perception of firms to depreciation shocks as permanent, and hence adjust their prices more rapidly, may illustrate the directional asymmetry of the NEER index effect on CPI inflation, notably when the exchange rate was used as a nominal anchor, see Krugman (1989).

Adding the short-term interest rate as a second low-frequency regressor in a PL-MIDAS model reveals a threshold non-linearity in the inflation rate response to interest rate changes. Specifically, looking at the non-parametric estimates of the PL-MIDAS with its variability bounds of 95% reveals a level asymmetry regarding the effect of short-term interest rate on the inflation rate. A significant inflation-reducing impact appears only whenever the interest rate level is sufficiently high, beyond 12% in our sample. This little deflationary impact of interest rate on inflation rate declares an improvement over the weakened and insignificant effect observed in earlier periods, see Billmeier and Al-Mashat (2007) [1996–2005], Hachicha and Lee (2009) [1977–2006] and Abdel-Baki (2010) [1991–2009], among others. Nonetheless, this additional non-linearity has only a minor effect on the predictive precision of the PL-MIDAS over the SI-MIDAS, as R^2 has only improved by one percentage point.

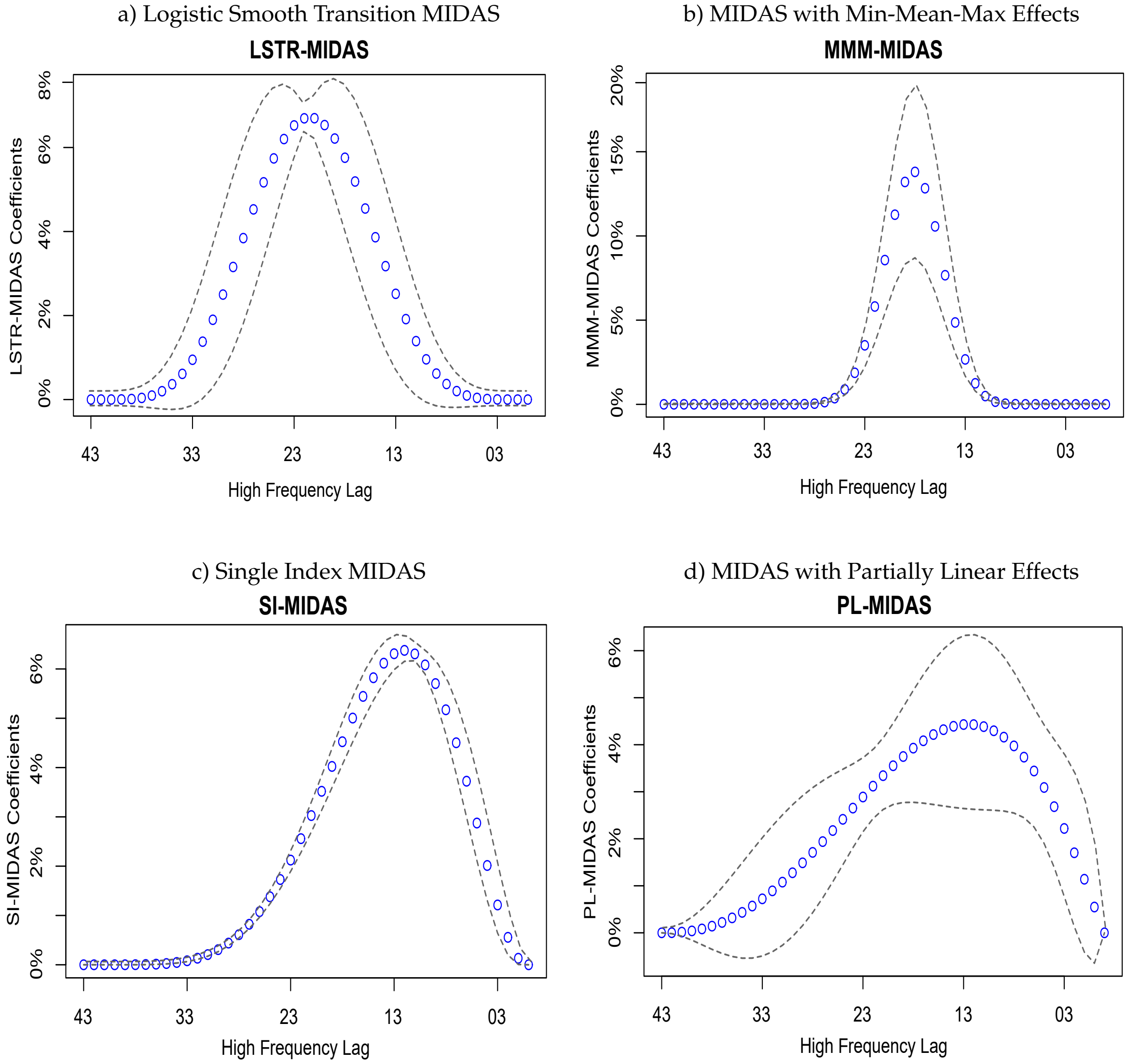
4.2. MIDAS Analysis of the CPI Inflation Dynamics

Figure 3 presents the empirical MIDAS restriction functions along with their 95% confidence bands for the estimated MIDAS specifications. The data-driven weights of the daily NEER index lags exhibit a humped-shape for the non-linear parametric regressions while display a memory-decay structure for the semi-parametric models. Both shapes are widely observed in the recent literature, see for example Ghysels et al. (2006), Foroni and Marcellino (2013) and Ghysels (2016). Observed also in Ghysels and Wright (2009), the hump-shaped weights indicate that the leverage of old NEER index lags diminishes as they move further into the past while the effect of most recent lags takes more time to pass-through to the realizations of inflation. Out of the eight weeks lags window, the six (three) weeks in the middle are the most important for explaining the next month inflation outcome as per the (MMM)LSTR-MIDAS regression. Similar to the pattern documented by Hanoma and Nautz (2019), the memory decay structure of the impact of daily exchange rate on the monthly inflation rate validates ex-ante beliefs that recent lags are more informative and thus capture more weight. According to the results of the semi-parametric MIDAS models the last six weeks are the most telling about the expected rate of inflation in the month to come.

Figure 3. The Empirical Restriction Functions for the Estimated MIDAS Models [%]

$$\pi_t = \mu + \sum_{r=1}^{2} \alpha_r \, \pi_{t-r} + g\left(\sum_{i=0}^{43} w_i \bigtriangleup log \; E_{s(t)-i}; \beta\right) + \varepsilon_t, \;\; s.t$$

$$\forall \; i, \; w_i = h(\gamma, \; i) = \frac{\psi(\gamma, \; i)}{\sum_{j=0}^{k} \psi(\gamma, \; j)} \;\; and \;\; \sum_{i=0}^{43} w_i = 1$$



Notes: The estimated MIDAS restriction functions $\{\hat{h}(\gamma, i)\}_{i=0}^{k}$ along with their 95% confidence intervals for the four variants of the non QL-MIDAS models.
The estimated high-frequency lags $\{\hat{h}(\gamma, i)\}_{i=0}^{k}$ show how much weight is placed on respective lag intervals starting from the current survey deadline $i = 0$ and counting backwards to the first day of the previous month $i = 43$.

4.3. Daily MIDAS Indicators of Inflation Rate

The MIDAS analysis of the previous subsection identifies the importance of high-frequency dynamics of exchange rate for understanding the monthly inflation rate empirics. Now, we investigate how these results can be useful in assessing the inflation dynamics also within the month. The MIDAS models can help in evaluating the unobservable inflation during the month if we assume that the inflation dynamics is the same on release and non-release days. [3] Following Monteforte and Moretti (2013), the estimated MIDAS models in Table 1 are used to predict for each day how inflation rate would respond to the new exchange rate information on that day. For each day $l = 0, \ldots, 21$ within a month $t = 1, \ldots, 212$, I construct a daily MIDAS indicator of inflation rate, $\hat{\pi}^{w}_{l,t}$, as per the next equation:

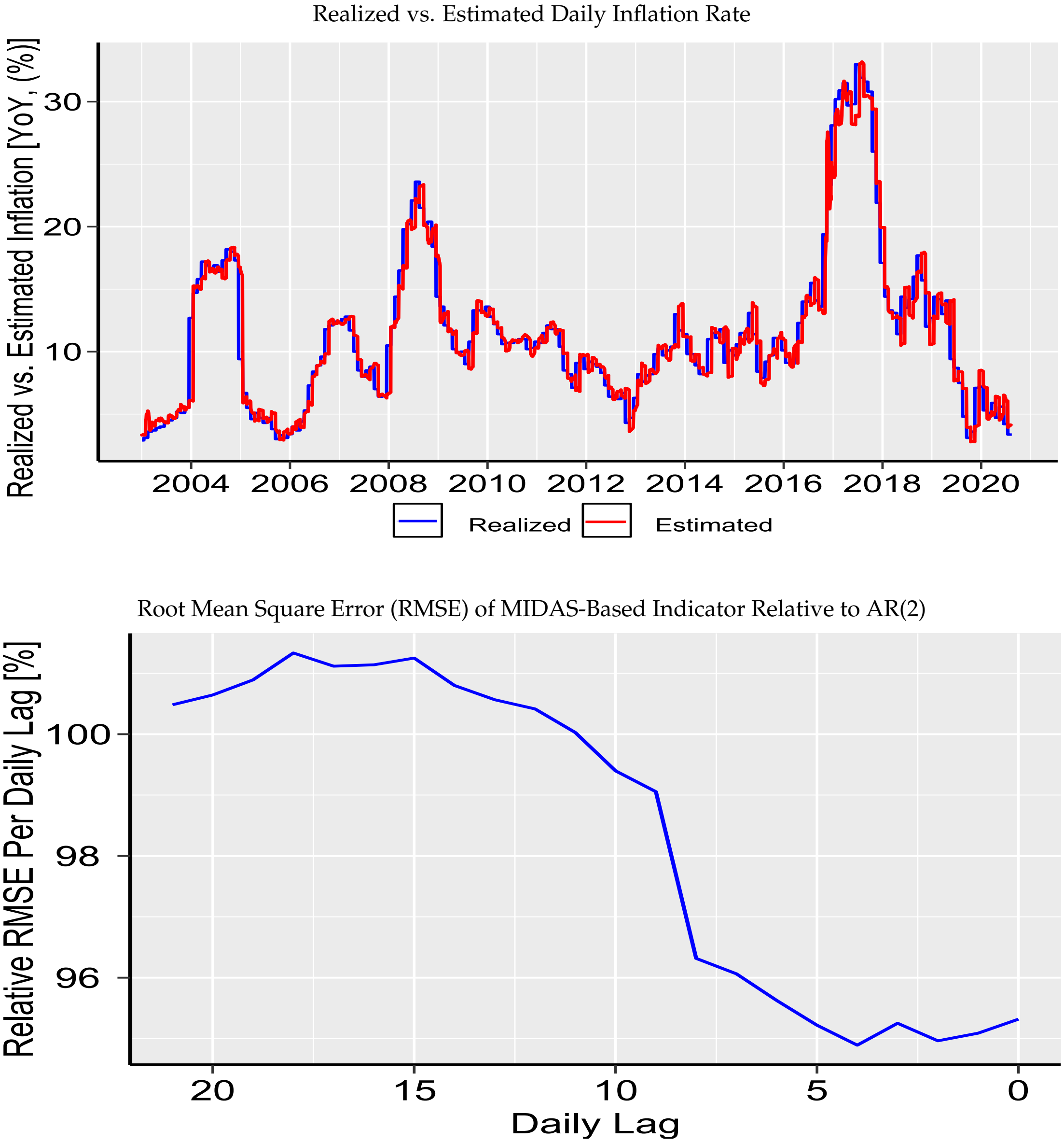
$$\hat{\pi}^{w}_{l,t} = \hat{\mu} + \sum_{r=1}^{2} \hat{\alpha}_r \, \pi_{t-r} + \hat{\beta}_1 \sum_{i=0}^{43} h(\hat{\gamma}, i) \bigtriangleup log \; E_{s(t)-i}, \;\; s.t \tag{10}$$

$$\forall \; i, \; h(\hat{\gamma}, i) = \frac{x_i^{\hat{\gamma}_1 - 1}(1 - x_i)^{\hat{\gamma}_2 - 1}}{\sum_{j=0}^{k} x_j^{\hat{\gamma}_1 - 1}(1 - x_j)^{\hat{\gamma}_2 - 1}}; \; x_i = \xi + (1 - \xi)\frac{i - 1}{k - 1} \; with \; \xi > 0 \; and \; \sum_{i=0}^{43} \hat{w}_i = 1$$

where $\hat{\pi}^{w}_{l,t}$ defines the estimated daily indicator of inflation rate valid l days before the release day in month t. This means that the daily indicator $\hat{\pi}^{w}_{l,t}$ and the monthly estimate $\hat{\pi}$ implied by the MIDAS model coincide on the release day ($l = 0$), by construction. Within the month ($l > 0$), the indicator is also based on the MIDAS model but only uses exchange rate data up to that day. The resulting MIDAS-based daily indicator of the monthly inflation rate based on the exchange rate is shown in the upper panel of Figure 4. The evolution of the estimated MIDAS-based inflation indicator reveals three observations. First, the estimated indicator can mimic the major developments in inflation rate quite well. Second, the lagged inflation rates are important for explaining next month inflation outcomes and therefore AR(2) is a very strong competitor. Third, it is still unclear how to evaluate the performance of our daily indicator within the month when inflation is simply unobserved.

[3] Alternatively, one could estimate for each day within a month a MIDAS regression separately, compare Monteforte and Moretti (2013). While this procedure would improve the fit of the daily indicator, the resulting MIDAS models do not differ significantly in our application. For the sake of simplicity, we therefore refrain from estimating 22 models and base our analysis on a single model.

Figure 4. The Performance of MIDAS Daily Indicators of Inflation Rate [%]



Notes: The upper panel of Figure 4 shows the daily MIDAS indicator of the next month inflation rate based on the new exchange rate innovations, with $\hat{\pi}^{w}_{l,t} = \hat{\mu} + \sum_{r=1}^{2} \hat{\alpha}_r \, \pi_{t-r} + \hat{\beta}_1 \sum_{i=0}^{43} h(\hat{\gamma}, i) \triangle log \; E_{s(t)-i}$, s.t $\forall \; i, \; h(\hat{\gamma}, i) = \frac{x_i^{\hat{\gamma}_1 - 1}(1-x_i)^{\hat{\gamma}_2 - 1}}{\sum_{j=0}^{k} x_j^{\hat{\gamma}_1 - 1}(1-x_j)^{\hat{\gamma}_2 - 1}}; \; x_i = \xi + (1-\xi)\frac{i-1}{k-1}$ with $\xi > 0$ and $\sum_{i=0}^{43} \hat{w}_i = 1$.

The lower panel of Figure 4 shows daily averages of RMSE ratios of daily MIDAS-based indicator relative to the AR(2) forecast. The lags are displayed chronologically starting with the first day after the release of the *previous* inflation figure ($i = 21$) while the last day refers to the current publication day ($i = 0$).

Following Monteforte and Moretti (2013), I compare the predictions of the daily indicator on non-release days with the end-of-month outcomes. This practical approach, yet, shows some limitations in our application as it assumes that all the movements in the next month inflation appears immediately after the previous release day. Accordingly, the performance of our daily indicator should exhibit some spurious forecasting errors at the beginning of the month while improves towards the end of the month. The lower panel of Figure 4 displays the evolution of the within-month forecasting performance of the MIDAS-based indicator relative to the $AR(2)$ model. The relative RMSE improves for the MIDAS-based indicator over the month reflecting that the RMSE on a day within the month cannot be calculated with respect to the unobservable next month inflation on that day but only with respect to the observable outcome at the end of the month. Similar pattern is obtained when the relative RMSEs are calculated weekly. Relative to the $AR(2)$, the RMSE of the MIDAS model, declines to 97% (95%) in the third (fourth) week of a given month.

5. Are Inflation Expectations in Egypt Well-Anchored?

In this section, we use our daily MIDAS-based indicator of inflation expectations to measure the degree of (de-)anchoring of inflation expectations in Egypt. The degree of (de-)anchoring is defined by the central bank's ability to steer inflation expectations of market participants. In my application, I use three standard tests to assess how inflation expectations, particularly in the longer terms, are firmly anchored. First, I measure the responsiveness of inflation expectations to the revisions of expert forecasts that cover a broad spectrum of macroeconomic variables, including different measures of exchange rate, see for example Gürkaynak et al. (2010) and Beechey et al. (2011). Second, I estimate the degree of inflation expectations' dependence on actual inflation outcomes, see for instance Ehrmann (2015) and Łyziak and Paloviita (2017). Third, I test the spill-over effects from short-term to long-term inflation expectations, see for example Dräger and Lamla (2013) and Ciccarelli et al. (2017). The dataset employed in this exercise is gathered monthly from the country reports of the Economist Intelligence Unit (EIU) for the period from 2010M01 till 2020M12.

5.1. Responsiveness of Inflation Expectations to Forecast Revisions

Well-anchored inflation expectations ought not respond to unexpected short-term economic developments. Therefore, a significant reaction of inflation expectations to forecast revisions may indicate a de-anchoring position. A precise estimation of the sensitivity of expectations to revisions of expert forecasts requires high-frequency inflation expectations data. Thanks to our daily indicator we can now regress the changes in the one period ahead MIDAS-based inflation expectations on the forecast revisions of ten macroeconomic variables that cover monetary, fiscal, financial, and trade areas gathered from the EIU country reports on a monthly basis. Table 2 shows that the daily inflation expectations indicator did only respond significantly to expert forecast revisions for the period following the currency floatation (see the p-value of F-statistic). Accordingly, one may conclude that Egypt inflation expectations were not fully anchored in that period. This result, however, needs to be taken with caution since it is predominantly based on short-term expectations. It would be useful, thence, if we could examine the degree of anchoring of longer-term expectations.

Table 2. The Response of Inflation Expectations to Forecast Revisions

	Full Sample 2010M01:2020M12		Before-Floatation 2010M01:2016M11		After-Floatation 2016M12:2020M12	
Intercept	0.021*	(0.012)	0.027	(0.018)	0.012	(0.014)
Industrial Production	0.002	(0.003)	0.000	(0.004)	0.014	(0.009)
USD/EGY Exchange Rate	0.061*	(0.031)	0.028	(0.032)	0.131**	(0.060)
EUR/EGY Exchange Rate	-0.054	(0.035)	-0.073	(0.051)	-0.031	(0.028)
JPY/EGY Exchange Rate	0.038	(0.040)	0.064	(0.052)	-0.033	(0.024)
Exports Volume	-0.001	(0.007)	0.004	(0.016)	-0.001	(0.005)
Imports Volume	0.003*	(0.002)	0.000	(0.002)	0.009**	(0.004)
Current Account	0.001	(0.004)	-0.004	(0.007)	0.010	(0.007)
Government Balance	-0.007	(0.009)	0.003	(0.016)	-0.030**	(0.014)
Lending Rate	0.004	(0.004)	0.005	(0.044)	-0.004	(0.006)
External Debt	-0.001	(0.003)	-0.001	(0.004)	-0.002	(0.004)
No of Observations	132		83		49	
R-Squared	0.04		0.04		0.36	
P-Value (F-Statistic)	0.87		0.98		0.05	

Notes: The table shows the response of one period ahead inflation expectations indicator to forecast revisions of main macroeconomic variables. White heteroskedasticity consistent standard errors are shown in parentheses. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted by ***, **, and *, respectively. P-values (F-Statistic) are for the hypothesis that all parameters are jointly zero.

5.2. Measuring Inflation Expectations Backward-Lookingness

Long-run inflation expectations, if firmly anchored, they shall not respond to developments in current inflation. Following Ehrmann (2015), we estimate the next regression:

$$\pi^e_{t,t+n} = \alpha + \beta\, \pi_{t-1} + \epsilon_t \tag{11}$$

where $\pi^e_{t,t+n}$ refers to inflation expectations formed in month t for year $n = 1, .., 4$ while π_{t-1} denotes the lagged actual inflation. Inflation expectations data are collected monthly from the EIU country reports for the period 2010M01 to 2020M12. Actual inflation rate data come from our daily MIDAS-based indicator one month before the deadline of the EIU forecasts release. Equation 11 is estimated by rolling regressions to examine possible variations in the expectations formation process as suggested by Łyziak and Paloviita (2017).

Rolling estimates of β, presented in Figure 5, show that short-run expectations are more driven by actual inflation outcomes than long-run expectations. Expectations de-anchoring can be clearly noticed since early 2020 for all horizons: forecasts are more dependent on the evolution of actual inflation and also more uncertain as indicated by the wider confidence bands. Except for the period around the pound floatation in late 2016, inflation expectations were generally well anchored. To disentangle whether the floatation decision has a lasting impact on inflation expectations we re-estimate Equation 11 as follows:

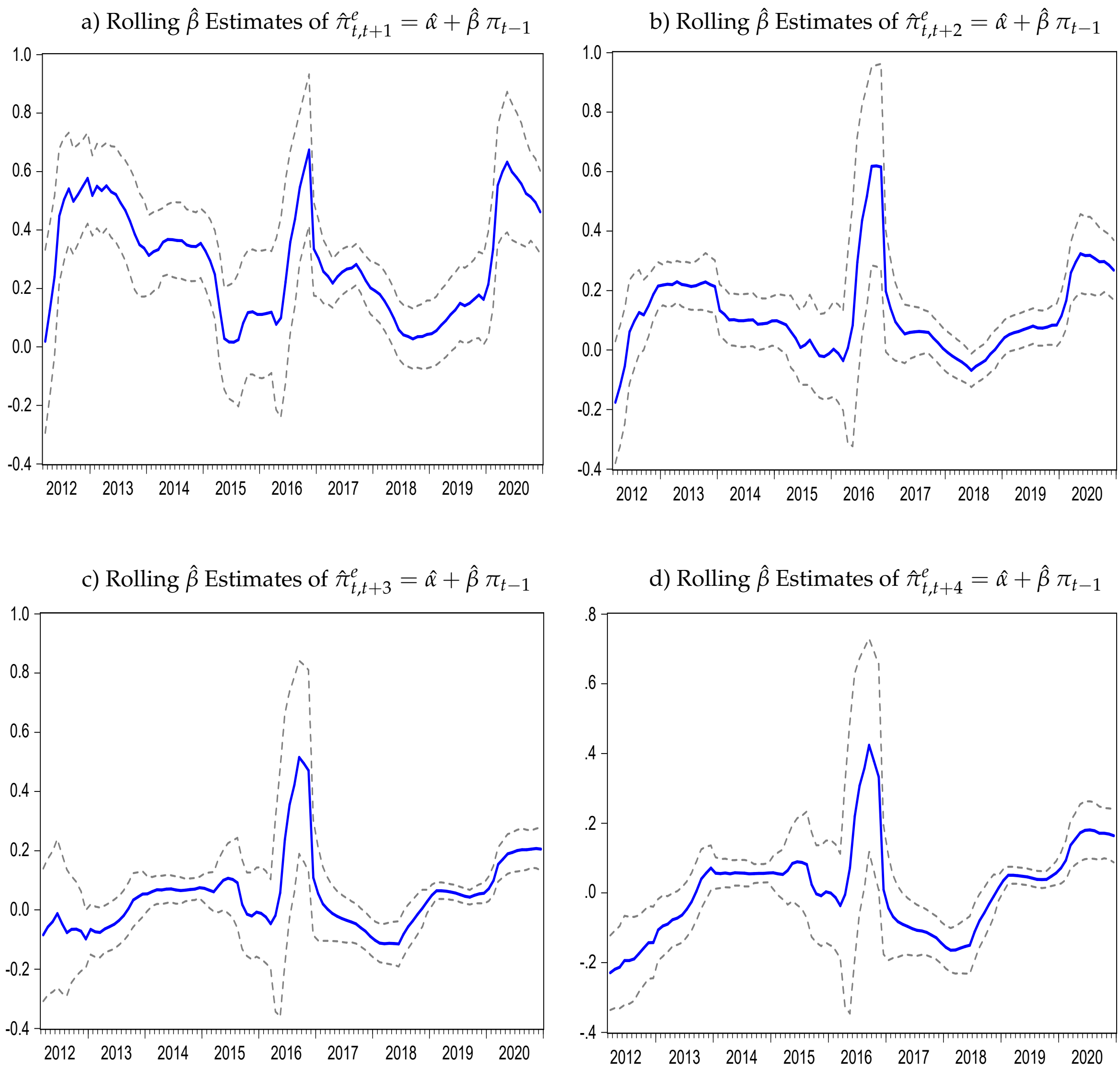
$$\pi^e_{t,t+n} = (1 - d^{pf})[\alpha_b + \beta_b\, \pi_{t-1}] + d^{pf}[\alpha_a + \beta_a\, \pi_{t-1}] + \epsilon_t \tag{12}$$

where d^{pf} is the pound floatation dummy which equals 0 up to 20016M11 and 1 thereafter. Table 3 shows that the floatation decision has increased the degree of inflation expectations backward-lookingness for the long-run forecast. The results of Wald test yet could not reject the null of equal slope before and after the floatation. Even when inflation is equal to zero, the expected value of the long-term inflation expectations post floatation is still less than the lower bound of the inflation target set by the CBE at that time (9% ± 3%). [4]

[4] The announced target was set to (13% ± 3%) in 2017M05 before it was revised to (9% ± 3%) in 2018M12.

Figure 5. Rolling Estimates of the Degree of Inflation Expectations Backward-Lookingness

$$\pi^e_{t,t+n} = \alpha + \beta\, \pi_{t-1} + \epsilon_t$$



Notes: Inflation expectations of $\pi^e_{t,t+1}$, $\pi^e_{t,t+2}$, $\pi^e_{t,t+3}$, and $\pi^e_{t,t+4}$ refer to the forecast horizons of one year, two years, three years, and four years ahead, respectively. Rolling estimates of the slope coefficient with 95% lower and upper confidence bounds dated at the end of each sub-sample. The size of the rolling window is fixed at 26 months and thus the sample of the first rolling regression is 2010M01-2012M02. Estimation is done using ordinary least squares with Newey-West heteroscedasticity and autocorrelation consistent HAC standard errors. Total number of observations used in estimation is 132 month covering the period from 2010M01 to 2020M12.

Table 3. Dependence of Inflation Expectations on the Actual Inflation Rate
$\pi^e_{t,t+n} = (1 - d^{pf})[\alpha_b + \beta_b\, \pi_{t-1}] + d^{pf}[\alpha_a + \beta_a\, \pi_{t-1}] + \epsilon_t$

	Whole Sample in Eq. 11			Whole Sample with the Floatation Dummy in Eq. 12						
	$\hat{\alpha}$	$\hat{\beta}$	R^2	$\hat{\alpha}_b$	$\hat{\beta}_b$	$\hat{\alpha}_a$	$\hat{\beta}_a$	R^2	$H0: \alpha_b = \alpha_a$	$H0: \beta_b = \beta_a$
$\pi^e_{t,t+1}$	6.56***	0.31***	0.52	6.34***	0.35***	6.07***	0.33***	0.52	0.03 [0.87]	0.04 [0.84]
	(0.36)	(0.03)		(1.09)	(0.12)	(1.24)	(0.05)			
$\pi^e_{t,t+2}$	6.84***	0.18***	0.36	5.73***	0.31*	6.24***	0.19***	0.40	0.08 [0.78]	0.41 [0.52]
	(0.28)	(0.02)		(1.64)	(0.19)	(0.74)	(0.03)			
$\pi^e_{t,t+3}$	7.26***	0.10***	0.15	5.77***	0.30**	5.79***	0.13***	0.41	0.00 [0.98]	1.24 [0.27]
	(0.27)	(0.02)		(1.30)	(0.15)	(0.49)	(0.02)			
$\pi^e_{t,t+4}$	7.38***	0.05**	0.04	6.83***	0.18	5.22***	0.11***	0.43	1.23 [0.27]	0.19 [0.67]
	(0.30)	(0.02)		(1.37)	(0.16)	(0.48)	(0.02)			

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Inflation expectations of $\pi^e_{t,t+1}$, $\pi^e_{t,t+2}$, $\pi^e_{t,t+3}$, and $\pi^e_{t,t+4}$ refer to the forecast horizons of one year, two years, three years, and four years ahead, respectively. Rolling estimates of the whole sample. The size of the rolling window is fixed at 26 months and thus the sample of the first rolling regression is 2010M01-2012M02. Estimation is done using ordinary least squares with Newey-West heteroscedasticity and autocorrelation consistent HAC standard errors. Numbers in parentheses below estimated coefficients are standard errors. Total number of observations used in estimation is 132 month covering the period from 2010M01 to 2020M12.

5.3. Investigating Spill-Overs from Short-Run to Long-Run Expectations

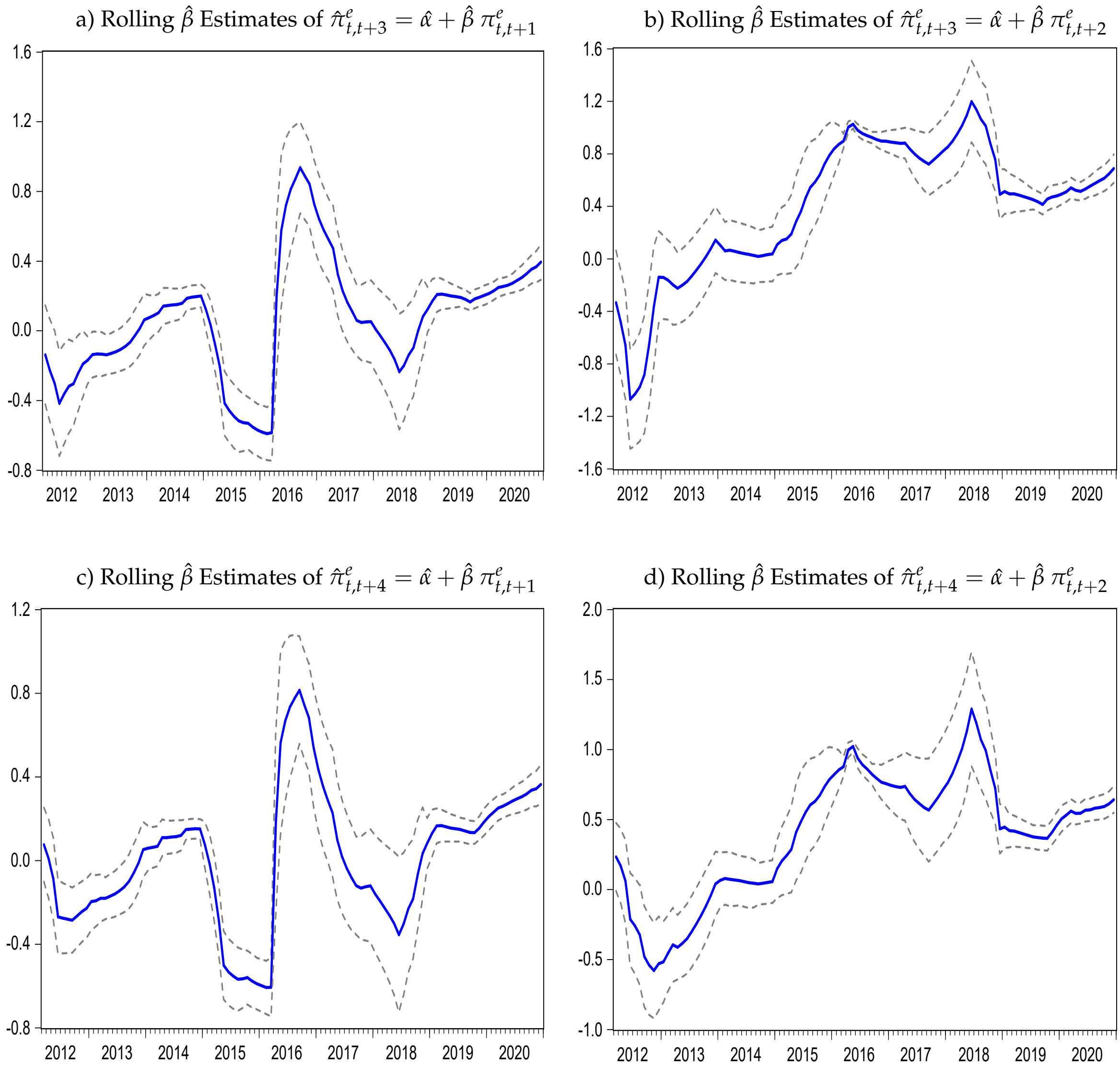
Again, longer term inflation expectations, when well-anchored, should not co-move with short-term expectations. Equation 13 identifies potential spill-overs from short-run $\pi^e_{t,t+m}$ to long-run $\pi^e_{t,t+n}$ inflation expectations while Equation 14 incorporates additional dummy d^{pf} to separate coefficients for the pre- and post-floatation periods.

$$\pi^e_{t,t+n} = \alpha + \beta\, \pi^e_{t,t+m} + \epsilon_t \;\text{ with }\; m < n \tag{13}$$

$$\pi^e_{t,t+n} = (1 - d^{pf})[\alpha_b + \beta_b\, \pi^e_{t,t+m}] + d^{pf}[\alpha_a + \beta_a\, \pi^e_{t,t+m}] + \epsilon_t \;\text{ with }\; m < n \tag{14}$$

The results in Figure 6 and Table 4 demonstrate that: the spill-over effects across inflation forecasts are larger than the dependence of expectations on lagged inflation; longer-term forecasts are less responsive to short-term forecasts than medium- to short-term forecasts; the impact of exchange rate floatation is more pronounced for the coupling between long- and short-term expectations than for the short- to medium-term forecast dynamics; the de-anchoring episode observed recently by the increasing degree of expectations backward-lookingness is even more certain for the cross-expectations interdependence.

Figure 6. Rolling Estimates of the Spill-Overs from Short-Run to Long-Run Expectations
$\pi^e_{t,t+n} = \alpha + \beta\, \pi^e_{t,t+m} + \epsilon_t$ where $m < n$



Notes: Inflation expectations of $\pi^e_{t,t+1}$, $\pi^e_{t,t+2}$, $\pi^e_{t,t+3}$, and $\pi^e_{t,t+4}$ refer to the forecast horizons of one year, two years, three years, and four years ahead, respectively. Rolling estimates of the slope coefficient with 95% lower and upper confidence bounds dated at the end of each sub-sample. The size of the rolling window is fixed at 26 months and thus the sample of the first rolling regression is 2010M01-2012M02. Estimation is done using ordinary least squares with Newey-West heteroscedasticity and autocorrelation consistent HAC standard errors. Total number of observations used in estimation is 132 month covering the period from 2010M01 to 2020M12.

Table 4. Dependence of Long-Term on Short-Term Inflation Expectations
$\pi^e_{t,t+n} = (1 - d^{pf})[\alpha_b + \beta_b\, \pi^e_{t,t+m}] + d^{pf}[\alpha_a + \beta_a\, \pi^e_{t,t+m}] + \epsilon_t$ with $m < n$

	Whole Sample in Eq. 13			Whole Sample with the Floatation Dummy in Eq. 14						
	$\hat{\alpha}$	$\hat{\beta}$	R^2	$\hat{\alpha}_b$	$\hat{\beta}_b$	$\hat{\alpha}_a$	$\hat{\beta}_a$	R^2	$H0: \alpha_b = \alpha_a$	$H0: \beta_b = \beta_a$
$\pi^e_{t,t+3} \sim \pi^e_{t,t+1}$	5.09***	0.32***	0.32	3.16	0.57**	4.15***	0.33***	0.52	0.15 [0.70]	0.72 [0.40]
	0.43	0.04		2.55	0.28	0.44	0.03			
$\pi^e_{t,t+3} \sim \pi^e_{t,t+2}$	2.37***	0.68***	0.64	1.87*	0.78***	2.12***	0.62***	0.77	0.05 [0.82]	1.57 [0.21]
	0.40	0.04		1.08	0.12	0.38	0.04			
$\pi^e_{t,t+4} \sim \pi^e_{t,t+1}$	5.30***	0.26***	0.19	3.35	0.54**	3.70***	0.29***	0.57	0.02 [0.89]	0.82 [0.37]
	0.50	0.05		2.48	0.27	0.40	0.03			
$\pi^e_{t,t+4} \sim \pi^e_{t,t+2}$	2.25***	0.64***	0.53	1.42**	0.82***	1.86***	0.56***	0.85	0.31 [0.58]	7.52 [0.01]
	0.48	0.05		0.73	0.09	0.28	0.03			

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Inflation expectations of $\pi^e_{t,t+1}$, $\pi^e_{t,t+2}$, $\pi^e_{t,t+3}$, and $\pi^e_{t,t+4}$ refer to the forecast horizons of one year, two years, three years, and four years ahead, respectively. Rolling estimates of the whole sample. The size of the rolling window is fixed at 26 months and thus the sample of the first rolling regression is 2010M01-2012M02. Estimation is done using ordinary least squares with Newey-West heteroscedasticity and autocorrelation consistent HAC standard errors. Numbers in parentheses below estimated coefficients are standard errors. Total number of observations used in estimation is 132 month covering the period from 2010M01 to 2020M12.

6. Concluding Remarks

Our results establish that exchange rate has asymmetric and de-anchored impacts on CPI inflation in a way that supports the adoption of flexible rather than rigid IT regime. Therefore, coordinated interventions in the foreign exchange market, distinctly when currency shocks are large and negative, are needed to reduce exchange rate volatility and anchor inflation expectations. This would allow domestic currency to adjust to its long-run equilibrium while attaining expectations tightly-anchored around its announced target. Inflation expectations anchoring, in return, requires an inclusive communication strategy, enhanced transparency plan, and an independent, credible, and accountable monetary authority.

For the institutional prerequisites of inflation targeting, Noureldin (2018) highlighted the danger of fiscal dominance and shallow capital markets. While the excessive monetization of budget deficit erodes the monetary policy credibility, shallow capital markets reduce the effectiveness of the interest rate as a monetary policy channel. The monetary transmission mechanism is still not complete according to the author because of the high percentage of unbanked adult population (67% according to the World Bank in 2018) and the large share of the informal sector in the economy (at least 30% per international estimates).

Appendix: Diagnostic Tests

Table A1. Results of the Augmented Dickey–Fuller Unit Root Test

	π_t	$\triangle\ log\ E_{s(t)-i}$
Constant Only		
DF-Stat	-3.49	-13.89
P-Value	0.01	0.01
Constant & Trend		
DF-Stat	-3.43	-13.89
P-Value	0.05	0.01

Notes: Results of the Augmented Dickey–Fuller (ADF) unit root tests for the monthly inflation rate and the daily exchange rate. Sample period is 2003M01 to 2020M08. π_t is the monthly seasonally non-adjusted inflation rate of total items where $\triangle\ log\ E_\tau$ is the percentage change in daily trade-weighted nominal effective exchange rate. Irrespective of the test specification applied, the results indicate that all the model variables are stationary.
Sources: Thomson Reuters Database with codes "EYCPCCPIF" and "JPEGEEN" for CPI inflation rate and NEER exchange rate, respectively. Data was last updated on September 15, 2020.

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