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# Inflation Volatility Effects on the Allocation of Bank Loans

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**Abstract**

This paper examines the distortionary effects of inflation volatility on the allocation of bank loans. We argue that inflation volatility would render bank managers to behave more conservatively in issuing new loans. In contrast, when inflation volatility is low, bank managers would have the latitude to lend more idiosyncratically. Using a large panel of commercial bank data gathered from 15 countries, we provide support for our hypothesis by demonstrating a strong negative relation between inflation volatility and the dispersion of loans-to-assets ratio. Similar results are obtained when we split the sample between EU and non-EU country groups. The robustness of our findings is confirmed by a battery of sensitivity checks.

**Keywords:** Bank loans, inflation volatility, cross-sectional dispersion, international panel data
**JEL classification:** C22, C23, D81, E51.

*Corresponding author; School of Management and Languages, Heriot–Watt University, Edinburgh EH14 4AS, UK. Tel: +44 (0)131 451 8373; E-mail: m.caglayan@hw.ac.uk. We are grateful for constructive comments and suggestions from two anonymous reviewers of this journal and the editor. The authors are also grateful to C.F. Baum, P. Beaudry and M.E. Schaffer for their specific comments as well as those of participants in the First Macroeconomic Research workshop Newcastle University Business School, 2015, Newcastle, UK; seminar talk at the National Chiao Tung University, 2015, Hsinchu, Taiwan. The standard disclaimer applies.

# 1 Introduction

Allocation of scarce resources to their most efficient use is a major problem for all societies. This is an important issue, as human wants are unlimited while resources are scarce and can have many alternative uses. In market-oriented economies, the price system is the primary mechanism through which resources are distributed across all potential alternatives. As long as firms and lenders can forecast the individual relative prices accurately, funds will continue to flow towards projects which are expected to yield the highest returns. However, under uncertainty, optimal allocation of resources fails.[1]

In this paper, we investigate the efficient allocation of banks' loans under inflation volatility.[2] Given we employ a large panel of commercial bank data collected from several countries and examine two different loan categories (net loans, and corporate and commercial loans), we provide broader evidence regarding the distortionary effects of inflation volatility on the allocation of banks' loans in comparison to a study that focuses on country-specific data only. Secondly, as we carry out the analysis for European Union (EU) and non-EU country panels separately, we compare and contrast the impact of volatility effects on the allocation of loans between these two groups. Thirdly, we investigate whether the volatility effects on the allocation of banks' loans have changed following the recent financial crisis.

In our analysis, we expect to find a negative association between inflation volatility and the cross-sectional dispersion of loans-to-total-assets ratio. That is i) during periods of high volatility, the cross-sectional dispersion of loans-to-assets ratio should narrow; and ii) during periods of tranquility, the dispersion of loans-to-assets ratio should widen. This association suggests that bank managers will behave similarly during periods of high inflation volatility and that they will have the latitude to behave more idiosyncratically when inflation volatility is low. The reasoning behind this prediction is that during

[1]Arrow (1962) argues that misallocation of resources can be an outcome of unwillingness to bear risks or equally could be due to a preference for risk, as risky enterprises will get less funding under uncertainty given the limitations of financial resources or markets.

[2]From here on, we use uncertainty and volatility interchangeably.

periods of high inflation volatility, due to excessive noise in the price system, bank managers would behave more conservatively in issuing new loans, as they cannot accurately evaluate the expected returns from lending.[3] In contrast, better quality information will lead to a more unequal distribution of lending across banks as bank managers can take advantage of more precise prediction of different lending opportunities.

The mechanism that we discuss suggests that price stability will favor the efficient allocation of loanable funds.[4] This issue is important, as commercial banks, specializing in overcoming frictions in the credit market by acquiring costly information on borrowers, are considered to be an important source of intermediated credit. In particular, it has been recognized that constrained firms are likely to rely heavily on bank loans, given their inability or limited access to the public securities markets. To that end, several economists have discussed that reductions in loanable funds could have a major impact on bank-dependent borrowers (e.g. small businesses) and may cause substantial reductions in their fixed investment expenditures or even lead them to bankruptcy (e.g. Gertler and Gilchrist, 1994 and Ferri et al., 2014).

To test whether our predictions receive support from the data, we constructed a large panel of commercial banks collected from the Bankscope database. Our sample covers the period between 1999-2013 and contains bank-level data from 15 countries including Argentina, Austria, Brazil, China, Denmark, France, Germany, Hong Kong, Luxembourg, Mexico, Russia, Switzerland, Turkey, the UK, and the US. The cross-country approach that we follow allows us to capture a sufficient number of inflation volatility bursts over the span of our data, as in this period inflation was lower and less volatile in comparison to the 70s and 80s. Furthermore, examining a cross-country panel we can gain a broader understanding of volatility effects on the allocation of banks' resources.

We carry out our empirical analysis by employing both fixed effects and an instrumental variables estimator based on the Generalized Method of Moments approach (IV-

[3]In this context, inflation volatility captures the noise in the price system.

[4]Beaudry et al. (2001) provide an analytical framework to examine the view that price stability allows an efficient allocation of fixed capital investment expenditures. They provide support for their claims using a panel of manufacturing UK firms.

GMM), which allows us to guard against the endogeneity problem. Both methodologies provide us with similar findings, which can be summarized as follows. Firstly, examining the full sample, we show that inflation volatility exerts a negative impact on the dispersion of both net loans-to-assets ratio, and corporate and commercial loans-to-assets ratio, providing support for our hypotheses. When we split the data between EU and non-EU countries, we observe that the same observation is valid for both country groups and for both loan categories. Lastly, we show that volatility effects for the EU-group has changed since the recent financial crisis. In particular, we find that while the adverse impact of inflation uncertainty on the allocation of commercial loans got stronger, this effect has weakened for net loans. In contrast, we find no significant change for the non-European countries for neither loan categories. Although the difference may be related to how quickly countries in each group recovered from the recessionary pressures induced by the financial crisis as well as various other macroeconomic shocks, further scrutiny would be useful to understand the underlying reasons.

To examine the robustness of our findings, we estimated our models for two different measures of inflation volatility. We also checked if the results are driven by countries which contribute the most or the least numbers of observations (US for the most; and Denmark, Germany, Hong Kong, and Turkey for the least). Separately, we dropped Germany and Switzerland from the analysis because the average commercial loan-to-asset ratios for these two countries were lower than the others. These exercises provided us with findings similar to our earlier observations. Furthermore, to overcome the missing variables problem, we used several control variables in our models. These control variables capture the level of inflation, growth rate of GDP, financial crisis effects, stock market volatility, oil price volatility, aggregate bank risk and return relationship, and year dummies. All models led to similar findings that inflation volatility has a negative impact on the allocation of scarce bank resources.

The paper is organized as follows. Section 2 discusses the related literature. Section 3 provides visual evidence on the link between inflation volatility and the cross-sectional distribution of bank loans, followed by our empirical models and the methodology. Section 4 presents the data and the uncertainty measures. Section 5 reports the results as well as the sensitivity checks. Section 6 concludes the paper.

## 2 Related Literature

One of the major issues in economics is the allocation of scarce resources to their most efficient use. Although the price system leads to an efficient allocation of resources, under uncertainty, this fails to materialize. To that end, theoretical researchers have expended considerable effort to show that uncertainty will affect fixed investment expenditures of firms. For instance, under (full or partial) irreversibility, several researchers have shown that an increase in the variance of the distribution of future rates of return from an investment project would raise the option value of waiting and cause delays in fixed investment expenditures (see for instance, Bernanke, 1983).[5] Hartman (1972) and Abel (1983) predicted a positive relationship between uncertainty and investment, where an increase in uncertainty about future prices raises the expected future return on a marginal unit of capital, and therefore raises the attractiveness of investment.

Several empirical researchers have shown that uncertainty has a negative impact on the level of a firm's fixed investment expenditures,[6] while a number of other studies have noted a positive or a non-linear relation between uncertainty and investment.[7] In contrast to other researchers, Beaudry et al. (2001), building on the framework suggested by Lucas (1973), emphasized the implications of uncertainty on firms' fixed investment expenditures rather than employment. Based on their analytical model they argued that variations in inflation uncertainty will distort the efficient allocation of firms' scarce

[5] Capital asset pricing models also suggest a negative relationship between investment and uncertainty. See for instance, Craine (1989).

[6] Among others see, for example, Leahy and Whited (1996); Bulan (2005) and Bloom et al. (2007).

[7] Sarkar (2000) found a U-shaped relationship between volatility and fixed investment. Mohn and Misund (2009) showed that oil price volatility has a positive effect on investment of international oil and gas firms. Czarnitzki and Toole (2011) showed that firm-level R&D investment falls in response to higher levels of uncertainty, but that patent protection partially mitigates the influence of uncertainty.

resources. In particular, their model implied that high (low) uncertainty will lead to a narrower (wider) cross-sectional distribution of firms' fixed investment rate as firm managers use less (more) precise knowledge on different investment opportunities. They provided support for their claims by scrutinizing a panel of UK manufacturing firms that covered the period between 1970-1990. Caglayan and Xu (2014) is the only other example in the literature that has focused on the association between volatility and the cross-sectional dispersion of firms' fixed investment expenditures. Using a panel of Japanese manufacturing firms, they also concluded that uncertainty distorts the efficient allocation of firms' fixed investment expenditures.

Baum et al. (2009) was the first study to examine the effects of uncertainty on the allocation banks' scarce resources. Different from Beaudry et al. (2001), they emphasized the importance of macroeconomic stability on the allocation of banks' loans and claimed that stability of the macroeconomic environment will favor more efficient allocation of loanable funds. To substantiate their claims, they used a large panel of US banks and showed that macroeconomic uncertainty (measured by the volatility of GDP growth or inflation) has a negative effect on the cross-sectional dispersion of total loans-to-assets ratio.[8] Subsequently, following Baum et al. (2009), Quagliariello (2009) and Calmès and Théoret (2014), too, examined the role of macroeconomic uncertainty on the cross-sectional dispersion of bank-specific resources. While the former study examined the role of macroeconomic stability on the efficient allocation of bank loans for a large panel of banks in Italy and the latter examined that for the top 6 banks from Canada and the top 20 banks from the US. Both studies arrived at similar conclusions that banks tend to behave more homogeneously during times of high macroeconomic uncertainty. All three studies used quarterly data and examined one country at a time.

When we survey the literature, we find that several researchers have examined the importance of the state of the economy on bank lending over the business cycle. For example, Gambacorta and Marques-Ibanez (2011), Brei and Schclarek (2013) and Brei

[8] They used either the contemporaneous conditional variance or a weighted average of the current and last three quarters conditional variances as a measure of macroeconomic volatility.

et al. (2013) found evidence that while government-owned banks increase their lending during periods of crisis, private banks' decrease their loans. Thus, these authors suggested that governments play an active counter-cyclical role in their country's banking systems. Ferri et al. (2014) suggested that stakeholder banks attempt to smooth financial conditions for their customers to maintain longer term borrower-lender relationship by conducting less procyclical loan supply polices, irrespective of the state of the economy or the financial markets.

Another strand of literature investigated the role of risk on bank loans. For example, Altunbas et al. (2010) found that banks with lower expected default frequency were able to offer a larger amount of credit and to protect their loan supply from monetary policy changes. Kosak et al. (2015) used a cross-country bank panel and found that the availability of high quality funds (tier 1 capital and retail deposits) and government support were crucial in continuous bank lending during the crisis periods. On a similar note, Delis et al. (2014) showed that when consumers' and analysts' anxiety increases, the supply of total bank loans in the US declines. Caglayan and Xu (2016) found that changes and volatility of sentiment have a negative and significant impact on banks' loan growth. They also highlighted that banks further reduce their loan growth when sentiment volatility reaches excessive levels.

Our investigation relates closely to Beaudry et al. (2001), as we focus our attention on the effects of inflation volatility on the allocation of banks' loans. As a consequence, our angle differs from that of Baum et al. (2009) who examined whether macroeconomic stability favors more efficient allocation of resources. Yet, empirically, we differ from all earlier studies in this genre. As our dataset contains information from 15 countries, we implement panel data methods to provide a broader perspective on the linkages between inflation volatility and banks' resource allocation problem compared to earlier studies, which depended on data from a single country.[9] We also compare and contrast uncertainty effects of bank loans between EU and non-EU country groups. Finally, we investigate

[9]Except for Calmès and Théoret (2014) who have used an EGARCH model, all other studies have based their claims on results obtained from the ordinary least square method.

whether this relation has changed following the recent financial crisis.

# 3 Empirical Analysis

Before discussing our empirical model, it would be useful to visualize the association between inflation volatility and the cross-sectional variance of both net loans-to-total-assets, and corporate and commercial loans-to-total-assets ratios. The top two graphs (a–b) in Figure 1 depict the variance of both net and corporate and commercial loans-to-assets ratio against inflation volatility for the full sample. The remaining four graphs (c–f) plot the same variables for the EU and non-EU countries. In all cases, we see that there is a negative correlation between inflation volatility and the cross-sectional dispersion of banks' loan-to-asset ratio for the full sample as well as both country groups. Although these figures provide a visual evidence of a negative association between inflation volatility and the cross-sectional dispersion of banks' loans-to-asset ratio, given that we are examining this relationship for several countries and that these countries could be subjected to country-specific shocks, a formal empirical investigation should be carried out before acknowledging such an association. Furthermore, besides country-level fixed effects, one has to consider the impact of various other factors that may distort our observations. In the next sections, we present our findings and carry out a battery of sensitivity checks to confirm the robustness of our observations.

## 3.1 Empirical Model

Our hypothesis and empirical investigation is similar to that in Beaudry et al. (2001). According to this view, when inflation volatility is low, the price mechanism will be operational. In such circumstances bank managers can rank projects with respect to one another and allocate scarce funds to their best use. However, if inflation volatility is high, because of the high noise in the signal, the price mechanism cannot be effectively used to extract information about the worthiness of the projects. As a consequence, banks become conservative in their lending activities and behave similarly. This behavior of bank managers can be captured by observing the association between the cross-sectional dispersion of loans-to-assets ratio and inflation volatility. Hence, an increase in inflation volatility should lead to a narrowing of the cross-sectional dispersion of the loans-to-assets ratio, and *vice versa*. To provide support for this hypothesis, we examine a panel of commercial banks gathered from several countries and use the following model:

$$Disp_{j,t}(Loans/TA) = \alpha + \beta_1 \hat{h}_{j,t} + \nu_j + \epsilon_{j,t}, \tag{1}$$

where the dependent variable, $Disp_{j,t}(Loans/TA)$, captures the dispersion of loans-to-total-assets ratio for country $j$ at time $t$. The dependent variable is computed for two different categories of loans: i) net loans and ii) corporate and commercial loans. The explanatory variable, $\hat{h}_{j,t}$, is a measure of time-varying country-specific inflation volatility. We measure inflation volatility by the conditional variance from an ARCH/GARCH model for the log difference of the consumer price index. We use within year inflation variance as an additional proxy to check the robustness of our findings. Details on volatility proxies are given in section 4.1.

Although our model is fairly simple, one needs to consider the fact that the data are gathered from several countries, indexed by '$j$'. If we were to pool all the data together and did not differentiate across cross-section and time series observations, the coefficient estimates from the pooled regression model would be biased. To overcome this problem, we allow for country-specific time-invariant fixed effects, $\nu_j$, in our regression model.[10,11] The last term in the model, $\epsilon_{j,t}$, denotes the idiosyncratic error associated with country $j$ at time $t$. In estimating the model, we use robust standard errors to control for the heteroscedasticity and within-panel serial correlation in the error term.

Estimating the above fixed effects model, we expect that the coefficient associated with the volatility measure, $\beta_1$, will take a negative sign. However, this is a naive model

[10] Hsiao (2014) is the standard reference to panel data methods.
[11] The Hausman test indicates that a fixed effects model should be used rather than a random effects model.

and one has to include various control variables into the model to avoid misspecification error. Exclusion of such variables can bias the results and lead one to wrongfully conclude in favor of the second moment effects. In particular, inclusion of second moment effects in an model without the corresponding level variable may lead the researcher attribute an impact to the volatility variable that is actually explained by the first moment.[12] Hence, except for the benchmark model, our models always contain the rate of inflation ($Inflation$). Furthermore, we augment the model with several control variables including GDP growth rate ($\Delta GDP$), a step dummy to capture the level effect of the recent financial crisis ($dumFC$), as well as an interaction term between the financial crisis dummy and the uncertainty measure ($dumFC * \hat{h}$) to capture if volatility effects has changed following the recent financial crisis.

Besides the aforementioned variables, we introduce four more control variables into the model, two of which capture volatility in the i) stock markets ($Vol_{Stock}$) and ii) oil prices ($Vol_{Oil}$) and the other two capture country-specific average iii) bank risks ($Bank_{Risks}$), and iv) bank returns ($Bank_{Returns}$). The former two variables capture volatility effects that emanate from the financial and commodity markets (gauging the stability of the macro economy), and the latter two allow us to control for the average risk-return appetite in the banking sector.[13] The final model takes the following form:

$$Disp_{j,t}(Loans/TA) = \alpha + \beta_1 \hat{h}_{j,t} + \boldsymbol{\gamma} \boldsymbol{Z_{j,t}} + \nu_j + i.year_t + \epsilon_{j,t} \quad (2)$$

In equation (2), $\boldsymbol{Z}$ denotes a vector of control variables containing $Inflation$, $\Delta GDP$, $dumFC$, $dumFC * \hat{h}$, $Vol_{Stock}$, $Vol_{Oil}$, $Bank_{Risks}$, and $Bank_{Returns}$. Here, the effect of GDP growth ($\Delta GDP$) on the dispersion of loans-to-asset ratio is ambiguous. For instance, in an expanding economy if new credit were to increase uniformly across all banks, then the dispersion of loans-to-assets ratio should not change. However, if new

[12] See for instance Huizinga (1993) for a discussion along these lines.

[13] We should stress that bank-level variables cannot be used in the model as we are examining the cross-sectional dispersion of banks' loans-to-assets ratio. To circumvent this problem, we introduced average bank profitability and bank profit volatility into the model so that the average risk-return relationship in the sector could be controlled for.

credit were to be extended by certain banks more than others then the dispersion would be positively effected as growth rate of GDP varies over time. The variable $dumFC$ is a step dummy set to 1 if the year is greater than 2007. This dummy captures whether the (mean) dispersion of loans-to-assets ratio has changed after the financial crisis.[14] Although we do not have a strong view, one may expect a positive sign on the step dummy because substantial amounts of funds have been injected into the financial markets following the crisis. In contrast, it is also possible to argue for a negative coefficient, as banks curtail their supply of loans during the crisis periods despite the efforts of the Central Banks and the governments (see for example, Puri et al., 2011, and Delis et al., 2014). The interaction term ($dumFC * \hat{h}$) allows us to examine if the slope coefficient associated with inflation uncertainty has changed following the financial crisis. A negative (positive) coefficient would suggest that following the financial crisis the adverse impact of volatility on the allocation of bank resources has strengthened (weakened).

We gauged stock market ($Vol_{Stock}$) and oil price volatility ($Vol_{Oil}$) by implementing ARCH/GARCH methodology. Although one may expect that stock market volatility would have a positive effect on the dispersion of banks loans, this effect could as well be negative. For instance, if banks were to extend credit to firms with high quality investment opportunities, even though those firms could not raise equity finance in periods of high stock market volatility, the dispersion of banks' loan-to-asset ratio would widen. However, if stock market volatility were to signal an all inclusive unrest in the financial markets, then the dispersion of loans would narrow, as banks tend to behave more conservatively in extending loans during periods of turmoil. The effect of oil price volatility on the dependent variable is expected to be negative, as an increase in oil price volatility implies an increase in turbulence in the macroeconomic environment leading to conservative bank lending behavior. Lastly, we expect that average bank risks should have a negative effect, and average bank returns should have a positive effect on the dispersion of loan-to-asset

[14] We also used a financial crisis dummy which is set to 1 if year is 2008 and 2009. This event dummy did not affect our results. Hence, we continued our analysis with the post crisis step dummy, as it is meaningful to examine to what extent bank behavior has changed following the financial crisis rather than just during the crisis years.

ratio.[15]

Overall, the inclusion of the control variables should not affect the sign and significance of the coefficient associated with inflation volatility, $\beta_1$, through which we discuss the adverse effects of inflation volatility on the allocation bank resources. Also note that our widest model includes year dummies, $i.year$, which controls for the remaining idiosyncratic shocks that may effect the relationship.

To guard against the potential endogeneity of the explanatory variables, we present the results based on IV-GMM.[16] In estimating our models, we used first and second lags of inflation, inflation volatility, and interest rate series as instruments. To test for the validity of the instrument set, we computed J-statistic of Hansen (1982) and reported the associated p-value in each corresponding table. In all cases this test showed that the instruments are orthogonal to the error term so that we do not raise this issue again to avoid repetition. In all of the models we report robust standard errors to allow for arbitrary heteroscedasticity and autocorrelation in the idiosyncratic error term (see for example, Baum, 2006; Baum et al., 2007).

# 4 Data

To carry out our investigation, we extract data from the Bankscope database which is collected and harmonised by Bureau van Dijk. The Bankscope is one of the most comprehensive, global database of banks' financial statements. From this database, we collect four bank-level series including banks' net loans, corporate and commercial loans, net incomes and total assets.

Although the Bankscope provides information on banks throughout the world, we restrict our attention to data from 15 countries for consistency purposes. In particular, to be in the final sample, we required that each country should contribute at least 20 banks at

[15]We proxy bank risks by the average annual variance of bank returns, and we proxy bank returns by the average annual bank returns.

[16]See Baum (2006); Baum et al. (2007); Schaffer (2012) on IV-GMM methodology.

any point in time, so that we have an accurate measure of the cross-sectional variability of loans-to-assets ratio. Furthermore, we required that banks should provide data on both net loans, corporate and commercial loans. As a consequence, these restrictions led us to focus on bank-level data from the following fifteen countries including Argentina, Austria, Brazil, China, Denmark, France, Germany, Hong Kong, Luxembourg, Mexico, Russia, Switzerland, Turkey, the UK, and the US. Using this dataset, we utilize bank-level information on more than 9,000 commercial banks across all countries to generate our dependent and the control variables. The bank-level data are extracted on an annual frequency and span the period between 1999 and 2013.

To carry out our analysis we extract country-specific macro data from the Datastream database including consumer price index, gross domestic product ($GDP$), stock market prices for all 15 countries as well as West Texas Intermediate oil price. Except for $GDP$ series, which is on a quarterly basis, all remaining series are extracted on a monthly basis. Having a large number of observations is useful as we implement ARCH/GARCH methodology to compute volatility measures using inflation, stock market return and oil price series. The data span the period between 1975-2013.

Upon constructing the net loans-to-total-assets ratio ($NLTA$) and corporate and commercial loans-to-total-assets ratio ($CCTA$) series, we check for potential outliers. We trim the top and the bottom 2.5 percentile of the loans-to-assets ratio distribution to remove the outliers from our sample.[17] After imposing these restrictions, the final span of the data for some countries turned out to be shorter than the period we initially extracted from the Bankscope database.

Table 1 provides the basic information on our bank data for each country. It should be noted that while some countries contribute as many as 7,000 banks (US) into the final sample, some others contribute as few as 20 banks (Hong Kong (20), Luxembourg(20),

[17]This trimming provided us with a sample such that the net loans-to-asset ratio is bracketed between 6% *vs.* 88%. Given the suggestion of a referee, to check whether the results are not driven by bundling of observation near the top or the lover bounds, we carried out the analysis after trimming the top and the bottom of the distribution at the 5th percentile. This trimming led us to a sample where the net loans ratio was between 15% *vs.* 85%. The results from this narrower data, which we suppress to conserve space, were similar to those we report here and they are available upon request.

Mexico (20) and Turkey (21)). Although this seemingly large variation in bank numbers across countries may be worrying, the average net loans-to-total-assets ratios, $\mu_{NL}$, happens to range between 40% and 60%, across all countries.[18] Similarly, the average standard deviation of net loans-to-assets ratio, $\sigma_{NL}$, across countries is around 20%. The lowest average standard deviation of net loans-to-assets ratio is observed in Turkey (13%) and the highest value is observed in Switzerland (26%). Interestingly, the average corporate and commercial loans-to-total-assets ratios, $\mu_{CC}$, differ substantially across countries. This could be due to different approaches in financing corporate investments (market *versus* bank based financing) or to the extent of industrialization and development across countries in our sample. When we observe the average $CCTA$ ratio we see that Switzerland and Germany stand out at the low end, whereas Denmark, Russia, Turkey and China are at the high end in this ranking. The table shows that the standard deviation of the corporate and commercial loans ratio, $\sigma_{CC}$, is lower than that of the net loans-to-assets ratio, $\sigma_{NL}$. Lower volatility in commercial loans could be driven by the fact that such loans are provided to firms with which banks have a long-run relation.

## 4.1 Generating a measure of inflation uncertainty

To estimate our model, we must gauge the extent of noise in the price mechanism for each country. To achieve that, we fit an ARCH/GARCH model to log difference of the monthly consumer price index series.[19] We should note that prior to estimating the model, we tested and confirmed the presence of ARCH effects using the Lagrange Multiplier (LM) test. Also, as shown in Table 2, due to data availability for some countries the beginning year starts later than others. The GARCH(p,q) model takes the following form:

[18] Luxembourg stands at the lowest end (26%) and the US stands at the highest end (62%).

[19] ARCH models are estimated for a longer period than the span of the data available from the Bankscope database per country so that we can use more observations to compute the parameters. Standard references are Engle (1982) and Bollerslev (1986).

$$\pi_t = \alpha + \Sigma_k^r \gamma_k \pi_{t-k} + \varsigma_i i.month_t + \epsilon_t, \qquad (3)$$
$$h_t = \omega_0 + \Sigma_k^p \omega_k h_{t-k} + \Sigma_k^q \omega_k \epsilon_{t-k}^2,$$

where $\pi_t$ denotes inflation, $i.month$ captures month effects, $\epsilon_t = \mu_t \sqrt{h_t}$ and $\mu_t$ is a zero mean, unit variance white noise process.

For each country, we estimate a variant of the above model while we fit an ARCH(p) or GARCH(p,q) model for the associated country, as depicted in Table 2. We find that for most of the countries a simple ARCH(1) or ARCH(2) model is sufficient to render the residuals free from higher order ARCH effects. For some others we use a low order GARCH(p,q) model rather than a higher order ARCH model. In all cases, we check whether the standardized residuals exhibit higher order autocorrelation and ARCH effects. Ascertaining that the selected model is well specified, we take the within year average of the estimated conditional variances to match the frequency of the bank-level data. This series is then used as a measure of noise in the price signals, which we denote as $\hat{h}_t$ in equations 1 and 2. Here, higher levels of conditional variance imply higher noise in the price mechanism, i.e. that the information content of prices has declined. In such circumstances, a decision maker will not be able to predict the viability of projects and will thus behave more conservatively.

The average conditional volatility varies within a broad range. We observe that in countries where the price system is more stable, the average conditional volatility of inflation is low, for instance see France, UK and the US in Table 2. However, for countries which went through episodes of significant economic turbulence during the period of investigation, inflation volatility bursts may be quite high. Such is the case for Argentina, China, Hong Kong, Turkey and Russia.[20] This pattern repeats itself when we consider the

[20]It should be noted that the table reports average inflation volatility per country over the period during which the country contributed to the bank-level data. For instance, inflation volatility in Brazil and Mexico is lower than some of the developed economies because the inflation experienced in these two countries were lower and more stable than the developed economies during the corresponding period

within year simple variance of monthly inflation. Although we do not provide details due to space considerations, when we check the volatility series more closely and compare across countries we see that inflation volatility can indeed increase substantially for a short period of time.[21]

To check for the robustness of our investigation, we measure inflation uncertainty by calculating the within year variance, denoted by $\hat{h}_t^r$. The last column of Table 2 gives the correlation between the two volatility series, denoted by $\rho_{\hat{h}_t,\hat{h}_t^r}$. We see from this column that the correlation is positive and high, but not perfect, ranging between 60% to 99%.

## 5 Results

This section presents a battery of results. Empirical models are first estimated using the fixed effects model and then the IV-GMM estimator to guard against the endogeneity problem. All models allow for country-specific fixed effects and our widest model allows for year effects. Robust standard errors are reported in all tables.

We first provide our results based on the full dataset. These results show that there is a negative association between inflation volatility and the cross-sectional variance of loans-to-total-assets ratio. We then split the data into European Union (EU) *versus* non-EU country groups and repeat the analysis. We find that the results based on both country groups yield a similar message that there is a negative association between inflation volatility and the cross-sectional dispersion of both category of loan ratios. These findings provide support for the hypothesis that volatility adversely affects the efficient allocation of scarce bank resources.

that each country contributed to the bank-level data.

[21] Bloom (2009) presents evidence that volatility bursts appear for short periods of time.

## 5.1 Effects of Uncertainty on the Allocation of Bank Loans: International Evidence

Table 3 presents our first set of results which are based on the fixed effects model. The dependent variable is the dispersion of the net loans-to-total-assets ($NLTA$) ratio. Estimations are carried out for the full sample. Column 1 presents the benchmark (naive) model where we allow inflation volatility as the sole explanatory variable. Here, we see that inflation volatility has a negative and significant effect (at the 1% level) on the cross-sectional dispersion of $NLTA$ ratio. In column 2 we augment the main model with the level of inflation ($Inflation$) and in column 3 we further add GDP growth rate ($\Delta GDP$). In both columns, the coefficient associated with inflation volatility is negative and highly significant. We also observe that the level of inflation takes a negative coefficient in both columns, yet it is significant at the 10% level in column 3 only. In these two columns and in what follows, the inclusion of the first moment variable along with its second moment does not affect the sign and the significance of volatility effects on the dispersion of net loans-to-assets ratio.[22]

Next, we consecutively add three more variables to the model. In column 4, we introduce the financial crisis step dummy ($dumFC$) to examine if the average dispersion of $NLTA$ ratio has changed following the financial crisis. In column 5, we allow for an interaction term between inflation volatility and the step dummy ($dumFC * \hat{h}$) so that we can examine whether the extent of the impact of inflation volatility on the dispersion of $NLTA$ ratio has changed after the financial crisis. In this case, the coefficient associated with financial step dummy ($dumFC$) is insignificant. In other words, our model does not provide support for a shift in the dispersion of net loans-to-assets ratio after the financial crisis. We also find that the coefficient associated with the interaction term ($dumFC * \hat{h}$) is insignificant. Hence, we conclude that the relationship between volatility and the dispersion of the net loans-to-assets ratio did not change after the financial crisis.

[22]Huizinga (1993) argues that the exclusion of the first moment might wrongfully lead the researcher to attribute a significant role to the second moment.

In column 6, we add year dummies. In column 7, we remove year dummies and augment the model with stock market, and oil price volatility measures and the two variables that control for banks' average risk-return preferences. In column 8, we reintroduce year dummies into the model. We find that the impact of stock market volatility is positive but only significant at the 10% level in column 7. The positive sign associated with stock market variability is possibly capturing an expansion in bank lending behavior as other sources of finance, especially equity financing, become less desirable due to increased turbulence in the stock markets. Variables that summarize bank risk-return relationship and oil price volatility do not assume a significant effect. Overall, the results from columns 6-8 show that inflation volatility has a robust negative impact on the dispersion of loans supporting our claims.

In Table 4, we turn our attention to examine the link between inflation volatility and the cross-sectional variance of corporate and commercial loans-to-total-assets ($CCTA$) ratio. The results given in this table provide similar insights as in Table 3. We find that the coefficient associated with inflation volatility is negative and significant at the 1% level in all columns except for the last column in which year dummies are included in conjunction with the additional control variables. Overall, the results presented here are supportive of the claim that inflation volatility adversely affects the allocation of banks' scarce resources.

Table 4 also shows that the level of inflation has a negative and significant impact on the dispersion of $CCTA$. This finding is sensible as many researchers have provided evidence that higher inflation has a negative impact on the firms' fixed investment expenditures and productivity growth (see for example, Leahy and Whited, 1996; Bulan, 2005; Bloom, 2009). When we examine the role of financial crisis in the model, we do not observe any significant effect.[23] Neither the step dummy nor the interaction term assumes a significant role. Different from Table 3, we observe that stock market volatil-

[23]We should remind that given we are examining whether the relationship between inflation volatility and the dispersion of loans-to-assets ratio has changed following the crisis, our findings do not suggest that financial crisis does not affect the efficient allocation of resources.

ity has no longer any significant effect on the dependent variable. Yet the variable that captures average bank risks take a negative and significant coefficient at the 10% level. This suggests that an increase in bank risks induce more conservative lending behavior leading to a narrowing of the dispersion of loans-to-assets ratio.

We next estimate the model using IV-GMM approach to guard against the endogeneity problem. To conserve space, Table 5 presents IV-GMM results for our widest model. The first four columns provide estimates for the dispersion of $NLTA$ ratio and the last four columns examine the dispersion of $CCTA$ ratio. In each set we present estimates with and without the additional four controls in addition to inflation, $GDP$ growth rate, financial crisis step dummy and the interaction term as well as year dummies. For both loan types, we find that inflation volatility has a negative impact on the dispersion of loan-to-assets ratio and significant at the 5% level or better. We also find that the effect of inflation is always negative and significant for several columns. In column 5 of the Table, against our expectations, $\Delta GDP$ receives a negative and significant sign. However, in the remaining tables, as expected, the effect of $\Delta GDP$ on loan dispersion is found to be either positive and significant or insignificant. The rest of the control variables in the table, including the financial crisis step dummy and the interaction term, do not have a significant role in explaining the dispersion of loans-to-assets ratio.

At this point, as we presented our main results, it could be useful to consider our findings in conjunction with the findings reported in literature. Perusing the literature that examined bank lending behavior, we see that bank loans tend to decline after monetary and financial shocks, making it difficult for bank-dependent borrowers to rely on external finance.[24] Furthermore, research suggests that cyclicality of loans can hinder the efficient allocation of resources. For instance, during the upward phase of the cycle, resulting from a lowering of bank lending standards, due to increased competition and the underestimation of risk, loans may be granted to investment projects with marginally positive or even negative net present value. In contrast, during an economic downturn,

[24] See for instance, Gertler and Gilchrist (1994) and Ferri et al. (2014).

even investments with positive net present value can be rejected due to increased risk premiums, reflecting banks' increased risk aversion during such periods.[25] The change in banks' risk preferences over the business cycle can also lead to changes in banks' lending behavior. For instance, banks are expected to grant more loans during the upward phase of the cycle than the downward phase, because, in general, lenders suffer less from asymmetric information problems during the expansionary state of the economy. In addition, because monitoring costs change with the business cycle, this may further affect fluctuations in bank credit.[26] Our investigation shows that bank loans will not be allocated to their best possible use in periods of high inflation volatility. Our results also confirm that an increase in the level of inflation will have similar effects. As the evidence is gathered from a broad cross-country panel dataset, our investigation clearly demonstrates the importance of price stability in achieving efficient allocation of bank loans in both emerging and developed economies.

### 5.2 Uncertainty Effects on the Allocation of Bank Loans: EU *versus* non-EU countries

In this section, we split our data into EU (Austria, Denmark, France, Germany, Luxembourg and the UK) *versus* non-EU country groups (Argentina, Brazil, China, Hong Kong, Mexico, Russia, Turkey, Switzerland, and the US), and carry out the analysis for each group separately.[27] Table 6 presents the results for the dispersion of net loans-to-total-assets ratio for the EU (the first 4 columns) and non-EU (the last 4 columns) groups.

When we examine the coefficient estimates associated with inflation volatility, we see that it takes a negative coefficient for both EU and non-EU groups. This estimate is highly significant except in columns 6 and 8 for the non-EU group when year dummies are included in the model. As noted earlier, uncertainty effects are known to be short

[25] See for instance, Rajan (1994); Ruckes (2004); Puri et al. (2011) and Bassett et al. (2014).
[26] See Athanasoglou et al. (2014).
[27] See Ferri et al. (2014) who discussed differences between EU and non-EU banking sectors.

lived and be captured by the year dummies. Overall, the results in Table 6 suggest that an increase in inflation volatility will reduce the dispersion of net loans-to-total-assets ratio both in EU and non-EU countries. It is also noteworthy to point out that the point estimates associated with inflation volatility is greater for the EU group than the non-EU group. The difference between the two groups is possibly due to the greater role played by banks in Europe compared with that in the non-EU group.

When we turn to examine the role of the control variables, we see that the coefficient associated with inflation is always negative for both country splits and becomes highly significant in columns 1 and 3, suggesting that increases in inflation adversely affect the efficient allocation of bank loans. Likewise, the growth rate of GDP has a positive effect on the dispersion of net loans-to-assets ratio and this effect is significant in three cases, including columns 1, 2 and 4. This is, too, meaningful as growth would stimulate some of the banks to lend to a wider set of borrowers. However, we observe that stock market and oil price volatility measures and the controls that capture bank risk-return relationship do not have any significant effect on the dispersion of loan-to-asset ratio.

The financial crisis step dummy, which captures the change in the average dispersion of bank loans in the post crisis period, takes a positive and insignificant coefficient except for column 2 when the coefficient becomes negative and highly significant. This suggests that banks have became more stringent in their lending decisions following the financial crisis, reflected by the narrowing of the cross-sectional dispersion of net loans-to-assets ratio. But there is no firm evidence to that end.[28] Furthermore, we find that the interaction term between the step dummy and the uncertainty measure is always positive and highly significant for the EU countries. Hence, although the affect of inflation volatility on the dispersion of net loans-to-total assets ratio is still negative, following the financial crisis the size of this effect is smaller for the EU countries.[29] Nevertheless, for the non-EU group we do not find any difference between the two periods: the impact of inflation

[28]The discussion is based on the sum of the coefficients of $dumFC$ and the constant ($Cons$), which yields a greater negative intercept for the post crisis period.

[29]Observe that the sum of the interaction and inflation volatility coefficients is negative but smaller for the post-crisis period.

volatility on the dispersion of net loans ratio is similar before and after the crisis.

Table 7 presents the results on the dispersion of corporate and commercial loans ratio for both EU and non-EU countries. Similar to the case of the net loans, we find that inflation volatility has a negative and significant impact on the dispersion of corporate and commercial loans-to-assets ratio for both EU and non-EU groups. Only in column 4 we find that this effect is insignificant but still negative as expected. Insignificance of the uncertainty effect is, again, due to the inclusion of year effects, which capture the impact of a short lived uncertainty burst. Similar to the previous table, we see that the size of the coefficients associated with uncertainty effects are greater for the EU countries than the non-EU countries.

Inflation and GDP growth, in general, takes the expected sign, but they are not significant in any column. Step dummy does not take a significant coefficient, either. However, the interaction term is negative in all columns and highly significant for the EU-group. This suggest that the impact of inflation uncertainty on the cross-sectional variance of corporate and commercial loans-to-assets ratio becomes even stronger in the period that followed the financial crisis for the EU countries. That is banks became even more conservative in their lending decision on corporate and commercial loans during the post financial crisis period. This is sensible as corporate and commercial loans are the first item in line that the managers are most concerned with when the price signals becomes noisier. In contrast, the interaction term for the non-EU group does not receive a significant coefficient. This suggests that after the financial crisis the effects of inflation volatility on the allocation of banks' loans did not change in the non-EU countries. The table also shows that stock market volatility induces a wider cross-sectional dispersion of corporate and commercial loans. Yet, oil price volatility and bank average risk-return measures do not appear to have a significant effect on the dispersion of loans-to-asset ratio. Overall, the difference in uncertainty effects on the dispersion of $NLTA$ and $CCTA$ between EU and non-EU country groups is interesting and it may be explained by the difficulties that the EU countries have been experiencing since the recent financial crisis.[30]

We next implemented the IV-GMM approach for the models presented above. This approach yielded similar results regarding the uncertainty effects on the dispersion of corporate and commercial loans. Hence, we refrain from presenting them here to save space, but they are available upon request from the authors.

### 5.3 Robustness Checks using Alternative Volatility Measures

To further check the robustness of our findings, we re-estimated all of the models that we presented in Tables 3-7 using the within year variance of inflation.[31] This exercise returned similar observations regarding the effect of inflation volatility on the dispersion of both types of loans ratio: inflation volatility has a negative impact on the dispersion of loans-to-assets ratio. In what follows, we present our results obtained using the IV-GMM estimator for our general model followed by a discussion on further sensitivity analysis.

Table 8 presents a summary set of results for the full sample, the EU and non-EU country groups for both net and corporate and commercial loans. Observing the first row we see immediately that the effect of inflation volatility is negative and highly significant except for columns 4 and 7, providing support for our hypothesis. We also observe that the coefficient of inflation always takes a negative sign, which is significant in several cases. The coefficient associated with GDP growth is insignificant except in column 3 when it has a positive and significant effect. Of the remaining control variables, only stock market volatility assumes a significant positive effect on the cross-sectional dispersion of corporate and commercial loans ratio in column 8. The others, including oil price volatility, bank risk-return measures, do not have a significant effect.

When we turn our attention to the impact of financial crisis on the dispersion of loans to asset ratio. We observe that the step dummy is insignificant throughout the table.

[30]For instance, it took EU countries a very long period to achieve the pre-crises real GDP levels.

[31]The use of within year variance is a common practice implemented by many other researchers. For instance, see Barro (1996); Judson and Orphanides (1999) who have used such an approach to evaluate the effects of inflation uncertainty on output growth.

In contrast, the interaction term takes a significant coefficient on several occasions. The coefficient associated with the interaction term becomes positive and significant for the EU group as we examine its impact on the dispersion of net loans-to-assets ratio. This observation suggests that for the EU countries, although the overall effect is still negative, the impact of inflation volatility on the dispersion of $NLTA$ ratio has weakened during the post financial crisis period. When we inspect the effect of the interaction term for the case of corporate and commercial loans, we find that the interaction term receives a negative and significant coefficient in all models except from the non-EU group. This suggests that, in EU countries, the adverse effect of inflation volatility on the allocation of bank loans has become even stronger for the corporate and commercial loan category during the post-crisis period. These observations are robust across all models.

We continue our sensitivity checks by excluding some of the countries from our analysis. In particular, we checked if the results are driven by countries which contribute the most or the least numbers of observations (US for the most; and Denmark, Germany, Hong Kong, and Turkey for the least). Separately, to examine the relation between inflation volatility and the dispersion of $CCTA$ ratio, we dropped Germany and Switzerland from the sample as the average $CCTA$ ratios for these two countries were much lower than the others. Overall, the results from all sensitivity analysis were very similar to our earlier findings confirming our conjecture about the perverse role of inflation volatility on the allocation of banks' loans.

# 6 Conclusion

In this study, we examine the effects of inflation volatility on the efficient allocation of banks' scarce resources. To carry out our investigation, we use a large panel of cross-country bank data constructed for 15 countries including Argentina, Austria, Brazil, China, Denmark, France, Germany, Hong Kong, Luxembourg, Mexico, Russia, Switzerland, Turkey, the UK, and the US. The analysis is implemented for two different loan categories (net loans, and corporate and commercial loans). The analysis spans the period 1999-2013.

Using our dataset, we provide evidence that uncertainty exerts a negative effect on the dispersion of net loans-to-assets ratio and corporate and commercial loans-to-assets ratio. Our findings, which receive support from the full sample, EU and non-EU country groups, show that bank managers i) have the latitude to lend more idiosyncratically when inflation volatility is low, as they can predict returns from each project more successfully; ii) behave similarly during periods of high inflation volatility. This observation implies that, when inflation volatility is high, scarce bank resources will not be allocated efficiently. In this context, we also examine whether the observed relationship has changed following the recent financial crisis. We find that for the EU countries while the adverse impact of inflation uncertainty on the allocation of corporate and commercial loans got stronger, this link has weakened for the net loans. However, for the post financial crisis period, we find no significant change in the association between volatility and the allocation of loans for the non-EU countries for neither categories of loans.

The results presented in this investigation provide broad evidence that uncertainty distorts banks' efficient allocation of resources. These findings are important, as commercial banks are considered to be a vital source of intermediated credit, inefficient allocation of loanable funds would have a major impact on bank-dependent borrowers. As many economies are slow to emerge from the effects of the recent financial crisis, what we do not need is an inflationary cycle which would adversely affect the allocation of banks' loans. These results provide another reason to pay attention to price stability.

Overall, our observations suggests for several additional research questions that one may investigate using more detailed bank level datasets.[32] For instance, it would be interesting to explore whether the differences in loan-to-total-assets ratios of banks are due to the different characteristics of the underlying projects that are financed by the banks. More concretely, in addition to examining the behavior of corporate and commercial

[32] We would like to thank one of the anonymous referees suggesting these questions for future research.

loans, an examination of other loan categories such as household, real estate, agricultural loans and further disaggregation within each loan category could yield useful information regarding banks' lending behavior in response to changes in uncertainty. Another issue that deserves further examination is whether banks with different characteristics behave differently under uncertainty. For example, can liquidity, capitalization ratios, size, ownership of banks help one to explain the efficient allocation of loanable funds across banks? Lastly, the role of regulation on bank lending under uncertainty deserves a careful examination. We leave these issues for future work.

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Table 1: Descriptive Statistics for Loan to Assets Ratio

| Country | Years | $\bar{N}$ | max | min | $\mu_{NL}$ | $\sigma_{NL}$ | $\mu_{CC}$ | $\sigma_{CC}$ |
|---|---|---|---|---|---|---|---|---|
| Argentina | 1999-2013 | 45 | 56 | 38 | 41.64% | 16.29% | 15.15% | 11.37% |
| Austria | 2000-2010 | 28 | 34 | 21 | 46.14% | 23.47% | 31.56% | 19.35% |
| Brazil | 2005-2013 | 49 | 59 | 27 | 47.71% | 20.74% | 26.15% | 17.66% |
| China | 2007-2013 | 94 | 123 | 27 | 47.56% | 12.85% | 38.81% | 11.64% |
| Denmark | 1999-2003 | 22 | 23 | 22 | 56.56% | 16.62% | 50.41% | 17.88% |
| France | 1999-2013 | 56 | 83 | 26 | 53.26% | 23.76% | 34.21% | 19.75% |
| Germany | 2009-2013 | 24 | 27 | 22 | 47.20% | 23.99% | 7.25% | 10.78% |
| Hong Kong | 2011-2012 | 21 | 21 | 20 | 51.41% | 14.93% | 31.50% | 14.27% |
| Luxembourg | 1999-2012 | 61 | 90 | 20 | 26.37% | 18.28% | 21.29% | 17.24% |
| Mexico | 2004-2013 | 26 | 30 | 20 | 44.96% | 20.12% | 25.61% | 18.21% |
| Russia | 2002-2013 | 627 | 772 | 27 | 53.61% | 17.70% | 41.88% | 17.08% |
| Switzerland | 1999-2010 | 78 | 94 | 40 | 49.73% | 26.22% | 9.85% | 10.25% |
| Turkey | 2011-2013 | 22 | 22 | 21 | 60.12% | 13.30% | 40.30% | 16.29% |
| UK | 1999-2013 | 43 | 52 | 32 | 40.34% | 22.39% | 23.02% | 16.79% |
| US | 1999-2013 | 7170 | 7733 | 5958 | 61.70% | 15.00% | 11.15% | 8.31% |

Table 2: Descriptive statistics for Inflation Volatility

| Country | ARCH(q) | GARCH(p) | Period | $\hat{h}_t$ | $\hat{h}_t^r$ | $\rho_{\hat{h}_t,\hat{h}_t^r}$ |
|---|---|---|---|---|---|---|
| Argentina | 2 | | 1995-2013 | 0.5065 | 0.5307 | 0.9996 |
| Austria | 2 | | 1990-2013 | 0.1149 | 0.0713 | 0.9484 |
| Brazil | 1 | 1 | 1995-2013 | 0.0549 | 0.0474 | 0.8484 |
| China | 1 | 1 | 1975-2013 | 0.5558 | 0.4506 | 0.9546 |
| Denmark | 1 | 2 | 1980-2013 | 0.1137 | 0.1222 | 0.7037 |
| France | 1 | 1 | 1990-2013 | 0.0289 | 0.0317 | 0.7491 |
| Germany | 1 | 2 | 1985-2013 | 0.1232 | 0.0941 | 0.6253 |
| Hong Kong | 2 | | 1997-2013 | 0.6969 | 1.2755 | 0.9299 |
| Luxembourg | 1 | | 1990-2013 | 0.3422 | 0.5052 | 0.9819 |
| Mexico | 1 | | 1998-2013 | 0.0737 | 0.1280 | 0.6176 |
| Russia | 2 | | 1998-2013 | 0.3794 | 0.3149 | 0.9774 |
| Switzerland | 1 | | 1975-2013 | 0.1402 | 0.1626 | 0.8665 |
| Turkey | 2 | | 1982-2013 | 1.5345 | 0.7963 | 0.9119 |
| UK | 1 | 1 | 1995-2013 | 0.0487 | 0.1371 | 0.5922 |
| US | 1 | 1 | 1990-2013 | 0.0876 | 0.1001 | 0.6319 |

Notes: $\hat{h}_t$ denotes ARCH-GARCH based volatility. $\hat{h}_t^r$ denotes within year variance based volatility. $\rho_{\hat{h}_t,\hat{h}_t^r}$ denotes matched sample correlation between the two volatility measures.

Table 3: Effects of Inflation Volatility on the Dispersion of Net Loans-to-Total-Assets Ratio

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\hat{h}$ | -0.00161*** | -0.00173*** | -0.00152*** | -0.00149*** | -0.00181*** | -0.00186* | -0.00220*** | -0.00247** |
| | (0.000270) | (0.000270) | (0.000306) | (0.000383) | (0.000513) | (0.000926) | (0.000687) | (0.000884) |
| $Inflation$ | | -0.00111 | -0.00166* | -0.00153 | -0.00148 | -0.00100 | -0.00769* | -0.00731 |
| | | (0.00103) | (0.000783) | (0.000959) | (0.00101) | (0.00135) | (0.00390) | (0.00436) |
| $\Delta GDP$ | | | -0.000265 | -0.000233 | -0.000195 | -0.000232 | 0.0000877 | 0.000118 |
| | | | (0.000158) | (0.000136) | (0.000148) | (0.000271) | (0.000183) | (0.000298) |
| $dumFC$ | | | | 0.000644 | 0.00000937 | -0.00169 | 0.000627 | 0.00537 |
| | | | | (0.00194) | (0.00194) | (0.00307) | (0.00148) | (0.00825) |
| $dumFC * \hat{h}$ | | | | | 0.00528 | 0.00591 | 0.00554 | 0.00667 |
| | | | | | (0.00304) | (0.00431) | (0.00400) | (0.00441) |
| $Vol_{Stock}$ | | | | | | | 0.00169* | 0.00154 |
| | | | | | | | (0.000955) | (0.00171) |
| $Vol_{Oil}$ | | | | | | | -0.00000834 | 0.000223 |
| | | | | | | | (0.0000198) | (0.000343) |
| $Bank_{Risks}$ | | | | | | | -0.649 | 4.208 |
| | | | | | | | (23.72) | (28.04) |
| $Bank_{Returns}$ | | | | | | | 0.274 | 0.210 |
| | | | | | | | (0.268) | (0.292) |
| $i.year$ | | | | | | YES | | YES |
| $Country$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $Cons$ | 0.0406*** | 0.0409*** | 0.0419*** | 0.0415*** | 0.0411*** | 0.0417*** | 0.0356*** | 0.0192 |
| | (0.0000626) | (0.000322) | (0.000520) | (0.00128) | (0.00119) | (0.00199) | (0.00376) | (0.0214) |
| $N$ | 129 | 129 | 129 | 129 | 129 | 129 | 128 | 128 |
| $R^2$ | 0.021 | 0.024 | 0.059 | 0.063 | 0.083 | 0.133 | 0.134 | 0.179 |

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects of Inflation Volatility on the Dispersion of Corporate and Commercial Loans-to-Total-Assets Ratio

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\hat{h}$ | -0.00196*** | -0.00231*** | -0.00237*** | -0.00238*** | -0.00194*** | -0.00128*** | -0.00210** | -0.00137 |
| | (0.000424) | (0.000452) | (0.000499) | (0.000503) | (0.000247) | (0.000313) | (0.000820) | (0.000877) |
| $Inflation$ | | -0.00332*** | -0.00317*** | -0.00320*** | -0.00327*** | -0.00361** | -0.00478 | -0.00297 |
| | | (0.000689) | (0.000821) | (0.000836) | (0.00109) | (0.00149) | (0.00328) | (0.00459) |
| $\Delta GDP$ | | | 0.0000734 | 0.0000652 | 0.0000131 | -0.000212 | 0.0000804 | -0.000170 |
| | | | (0.000112) | (0.000105) | (0.0000907) | (0.000115) | (0.000178) | (0.000205) |
| $dumFC$ | | | | -0.000168 | 0.000707 | -0.00202 | 0.000699 | -0.00780 |
| | | | | (0.00150) | (0.00132) | (0.00276) | (0.00135) | (0.00567) |
| $dumFC * \hat{h}$ | | | | | -0.00728 | -0.00484 | -0.00689 | -0.00406 |
| | | | | | (0.00573) | (0.00503) | (0.00584) | (0.00558) |
| $Vol_{Stock}$ | | | | | | | -0.000187 | 0.000252 |
| | | | | | | | (0.000333) | (0.00126) |
| $Vol_{Oil}$ | | | | | | | 0.000000912 | -0.000237 |
| | | | | | | | (0.0000229) | (0.000307) |
| $Bank_{Risks}$ | | | | | | | -18.21 | -22.46* |
| | | | | | | | (15.29) | (11.69) |
| $Bank_{Returns}$ | | | | | | | -0.137 | -0.128 |
| | | | | | | | (0.247) | (0.252) |
| $i.year$ | | | | | | YES | | YES |
| $Country$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $Cons$ | 0.0239*** | 0.0250*** | 0.0247*** | 0.0248*** | 0.0253*** | 0.0278*** | 0.0287*** | 0.0299*** |
| | (0.0000981) | (0.000279) | (0.000492) | (0.00103) | (0.00109) | (0.00139) | (0.00201) | (0.00356) |
| $N$ | 129 | 129 | 129 | 129 | 129 | 129 | 128 | 128 |
| $R^2$ | 0.034 | 0.069 | 0.072 | 0.073 | 0.114 | 0.231 | 0.120 | 0.235 |

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effects of Inflation Volatility on the Dispersion of Net Loans-to-Total-Assets Ratio and Corporate and Commercial Loans-to-Total-Assets Ratio using IV-GMM

| | $NLTA$ | | | | $CCTA$ | | | |
|---|---|---|---|---|---|---|---|---|
| $\hat{h}$ | -0.00159*** | -0.00163*** | -0.00167** | -0.00199** | -0.00239*** | -0.00163*** | -0.00293*** | -0.00171** |
| | (0.000392) | (0.000574) | (0.000660) | (0.000820) | (0.000458) | (0.000495) | (0.000878) | (0.000805) |
| $Inflation$ | -0.000523 | -0.000180 | -0.00632** | -0.00594* | -0.00347*** | -0.00389*** | -0.00546** | -0.00460 |
| | (0.00161) | (0.00174) | (0.00306) | (0.00318) | (0.00108) | (0.000920) | (0.00273) | (0.00286) |
| $\Delta GDP$ | -0.000165 | -0.000231 | 0.00000318 | 0.0000840 | -0.0000127 | -0.000243** | 0.000159 | -0.000137 |
| | (0.000136) | (0.000192) | (0.000189) | (0.000234) | (0.000105) | (0.000111) | (0.000192) | (0.000212) |
| $dumFC$ | -0.000120 | -0.00277 | 0.000917 | -0.00171 | 0.0000967 | -0.00279 | 0.000217 | -0.00211 |
| | (0.00122) | (0.00211) | (0.00106) | (0.00260) | (0.00108) | (0.00202) | (0.00116) | (0.00206) |
| $dumFC * \hat{h}$ | 0.00640 | 0.00532 | 0.00379 | 0.00388 | -0.00271 | -0.00435 | -0.00115 | -0.00326 |
| | (0.00545) | (0.00549) | (0.00522) | (0.00552) | (0.00414) | (0.00468) | (0.00398) | (0.00472) |
| $Vol_{Stock}$ | | | 0.00148 | 0.00118 | | | 0.0000506 | 0.0000203 |
| | | | (0.000996) | (0.00137) | | | (0.000930) | (0.00109) |
| $Vol_{Oil}$ | | | -0.000000922 | 0.000172 | | | -0.00000843 | -0.000180 |
| | | | (0.0000189) | (0.000865) | | | (0.0000192) | (0.000912) |
| $Bank_{Risks}$ | | | -3.043 | 5.568 | | | -12.41 | -20.28 |
| | | | (19.36) | (19.87) | | | (16.48) | (16.64) |
| $Bank_{Returns}$ | | | 0.320* | 0.221 | | | -0.219 | -0.101 |
| $i.year$ | | YES | | YES | | YES | | YES |
| $Country$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $N$ | 127 | 127 | 126 | 126 | 127 | 112 | 126 | 126 |
| $R^2$ | 0.075 | 0.122 | 0.116 | 0.154 | 0.072 | 0.163 | 0.088 | 0.223 |
| *Hansen J test (p_value)* | 0.239 | 0.197 | 0.148 | 0.134 | 0.120 | 0.113 | 0.311 | 0.112 |

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effects of Inflation Volatility on the Dispersion of Net Loans-to-Total-Assets Ratio for EU and Non-EU countries

| | *EU* | | | | *NonEU* | | | |
|---|---|---|---|---|---|---|---|---|
| $\hat{h}$ | -0.0775*** | -0.105*** | -0.0721** | -0.108*** | -0.00140*** | -0.000943 | -0.001000** | -0.000670 |
| | (0.00514) | (0.0243) | (0.0187) | (0.0204) | (0.000351) | (0.000779) | (0.000354) | (0.000993) |
| $Inflation$ | -0.0266** | -0.0219 | -0.0203** | -0.0243 | -0.000893 | -0.000511 | -0.00297 | -0.00491 |
| | (0.00726) | (0.0128) | (0.00549) | (0.0191) | (0.000829) | (0.000972) | (0.00278) | (0.00322) |
| $\Delta GDP$ | 0.000737* | 0.00125*** | 0.00109 | 0.00166*** | -0.000252 | -0.000170 | -0.000260 | 0.00000650 |
| | (0.000332) | (0.000272) | (0.000594) | (0.000364) | (0.000166) | (0.000221) | (0.000173) | (0.000261) |
| $dumFC$ | 0.000732 | -0.00646*** | 0.00147 | 0.0163 | 0.000649 | 0.00177 | 0.000589 | 0.0115 |
| | (0.00283) | (0.00102) | (0.00424) | (0.0169) | (0.00228) | (0.00155) | (0.00207) | (0.00757) |
| $dumFC * \hat{h}$ | 0.0277*** | 0.0370*** | 0.0219* | 0.0430** | 0.00283 | 0.00117 | 0.00168 | 0.000884 |
| | (0.00402) | (0.00691) | (0.0105) | (0.0160) | (0.00265) | (0.00294) | (0.00292) | (0.00435) |
| $Vol_{Stock}$ | | | 0.00371 | 0.00351 | | | -0.000430 | -0.00194 |
| | | | (0.00242) | (0.00238) | | | (0.000941) | (0.00255) |
| $Vol_{Oil}$ | | | -0.0000220 | 0.00112 | | | 0.0000246 | 0.000419 |
| | | | (0.0000283) | (0.000583) | | | (0.0000188) | (0.000348) |
| $Bank_{Risks}$ | | | 39.44 | 29.55 | | | -10.21 | -13.88 |
| | | | (51.39) | (65.99) | | | (26.21) | (37.87) |
| $Bank_{Returns}$ | | | 0.356 | -0.998 | | | 0.0943 | 0.0684 |
| | | | (1.122) | (0.874) | | | (0.296) | (0.304) |
| $i.year$ | | YES | | YES | | YES | | YES |
| $Country$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $Cons$ | 0.0605*** | 0.0652*** | 0.0476*** | -0.0168 | 0.0348*** | 0.0329*** | 0.0358*** | 0.0102 |
| | (0.00219) | (0.00217) | (0.00646) | (0.0495) | (0.00150) | (0.00145) | (0.00365) | (0.0188) |
| $N$ | 55 | 55 | 55 | 55 | 74 | 74 | 73 | 73 |
| $R^2$ | 0.350 | 0.527 | 0.430 | 0.581 | 0.137 | 0.245 | 0.158 | 0.295 |

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effects of Inflation Volatility on the Dispersion of Corporate and Commercial Loans-to-Total-Assets Ratio for EU and Non-EU Countries

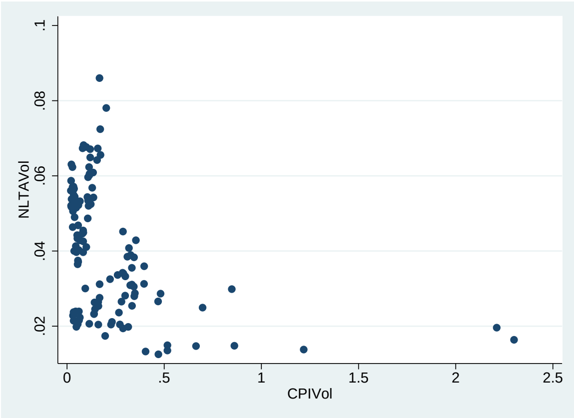
| | *EU* | | | | *NonEU* | | | |
|---|---|---|---|---|---|---|---|---|
| $\hat{h}$ | -0.0345*** | -0.0501* | -0.0399** | -0.0531 | -0.00208*** | -0.00121** | -0.00259** | -0.00200* |
| | (0.00623) | (0.0247) | (0.0110) | (0.0270) | (0.000290) | (0.000482) | (0.00110) | (0.000961) |
| $Inflation$ | -0.00570 | -0.00894 | 0.000932 | -0.0136 | -0.00300*** | -0.00288** | -0.00401 | -0.000700 |
| | (0.00568) | (0.0166) | (0.00721) | (0.0199) | (0.000805) | (0.000912) | (0.00245) | (0.00352) |
| $\Delta GDP$ | 0.000115 | 0.000228 | -0.0000739 | 0.000307 | 0.00000967 | -0.0000996 | 0.000156 | -0.0000390 |
| | (0.000258) | (0.000495) | (0.000494) | (0.000489) | (0.000111) | (0.000151) | (0.000171) | (0.000251) |
| $dumFC$ | 0.00429 | -0.00263 | 0.00518 | 0.0153 | 0.000432 | -0.00168 | 0.000702 | -0.00630 |
| | (0.00300) | (0.00671) | (0.00369) | (0.0261) | (0.00115) | (0.00266) | (0.00116) | (0.0103) |
| $dumFC * \hat{h}$ | -0.0419*** | -0.0412*** | -0.0556*** | -0.0336** | -0.00203 | -0.00116 | -0.000732 | 0.000634 |
| | (0.00614) | (0.00280) | (0.00560) | (0.00964) | (0.00281) | (0.00387) | (0.00355) | (0.00460) |
| $Vol_{Stock}$ | | | 0.00144 | 0.000888 | | | 0.000251 | 0.00255* |
| | | | (0.00113) | (0.00119) | | | (0.000477) | (0.00128) |
| $Vol_{Oil}$ | | | 0.0000480 | 0.000974 | | | -0.0000197 | -0.000234 |
| | | | (0.0000466) | (0.00154) | | | (0.0000113) | (0.000456) |
| $Bank_{Risks}$ | | | -18.62 | -22.75 | | | -18.04 | -10.60 |
| | | | (22.97) | (32.54) | | | (22.85) | (18.87) |
| $Bank_{Returns}$ | | | 0.689 | -0.804 | | | -0.216 | -0.209 |
| | | | (0.904) | (0.916) | | | (0.214) | (0.166) |
| $i.year$ | | YES | | YES | | YES | | YES |
| $Country$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $Cons$ | 0.0373*** | 0.0411*** | 0.0287** | -0.0216 | 0.0190*** | 0.0218*** | 0.0228*** | 0.0320 |
| | (0.00210) | (0.00222) | (0.00730) | (0.104) | (0.000955) | (0.00153) | (0.00236) | (0.0311) |
| $N$ | 55 | 55 | 55 | 55 | 74 | 74 | 73 | 73 |
| $R^2$ | 0.403 | 0.572 | 0.490 | 0.584 | 0.150 | 0.343 | 0.163 | 0.389 |

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

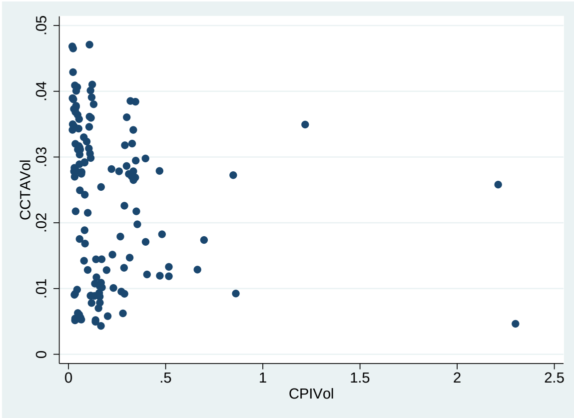
Table 8: Robustness Check: A Re-examination of the Effects of Inflation Volatility and Banks' Loan Dispersion using a Different Uncertainty Proxy and IV-GMM

| | *NLTA* | | | | *CCTA* | | | |
|---|---|---|---|---|---|---|---|---|
| | (*Full*) | | (*EU*) | (*NonEU*) | (*Full*) | | (*EU*) | (*NonEU*) |
| $\hat{h}^r$ | -0.00147** | -0.00176** | -0.100* | -0.000369 | -0.000903** | -0.00180* | -0.0102 | -0.00145** |
| | (0.000668) | (0.000747) | (0.0531) | (0.000655) | (0.000378) | (0.000958) | (0.0338) | (0.000586) |
| $Inflation$ | -0.000714 | -0.00744** | -0.0372* | -0.00464* | -0.00336*** | -0.00346 | -0.0180 | -0.000896 |
| | (0.00177) | (0.00331) | (0.0215) | (0.00280) | (0.000920) | (0.00323) | (0.0179) | (0.00293) |
| $\Delta GDP$ | -0.000194 | 0.000154 | 0.00312** | -0.0000239 | -0.000201 | -0.0000418 | 0.000123 | -0.0000132 |
| | (0.000187) | (0.000231) | (0.00158) | (0.000235) | (0.000123) | (0.000255) | (0.00158) | (0.000234) |
| $dumFC$ | -0.00197 | -0.00122 | -0.0140 | -0.00402 | -0.00263 | -0.00200 | -0.0104 | 0.000154 |
| | (0.00198) | (0.00240) | (0.00896) | (0.00301) | (0.00181) | (0.00288) | (0.00924) | (0.00231) |
| $dumFC * \hat{h}^r$ | 0.00257 | 0.00360 | 0.0456** | 0.000310 | -0.00827** | -0.00922** | -0.0224** | -0.000988 |
| | (0.00254) | (0.00278) | (0.0200) | (0.00305) | (0.00398) | (0.00393) | (0.0112) | (0.00339) |
| $Vol_{Stock}$ | | 0.00122 | 0.00461 | -0.00204 | | 0.000954 | 0.0000425 | 0.00319*** |
| | | (0.00135) | (0.00310) | (0.00159) | | (0.00114) | (0.00138) | (0.00121) |
| $Vol_{Oil}$ | | 0.000160 | 0.00126 | 0.000746 | | -0.0000776 | 0.000669 | -0.000168 |
| | | (0.000390) | (0.000973) | (0.000882) | | (0.000447) | (0.00105) | (0.000369) |
| $Bank_{Risks}$ | | 1.980 | -0.783 | -14.98 | | -18.96 | -10.72 | -12.21 |
| | | (19.41) | (67.01) | (24.78) | | (16.37) | (32.51) | (19.93) |
| $Bank_{Returns}$ | | 0.226 | -1.874 | 0.0595 | | -0.252 | -1.124 | -0.202 |
| | | (0.190) | (1.812) | (0.205) | | (0.204) | (0.795) | (0.187) |
| *i.year* | YES | YES | YES | YES | YES | YES | YES | YES |
| *Country* | YES | YES | YES | YES | YES | YES | YES | YES |
| $N$ | 127 | 126 | 49 | 72 | 127 | 126 | 54 | 72 |
| $R^2$ | 0.116 | 0.161 | 0.072 | 0.291 | 0.253 | 0.250 | 0.588 | 0.369 |
| *Hansen J test (p_value)* | 0.211 | 0.324 | 0.445 | 0.436 | 0.471 | 0.151 | 0.116 | 0.107 |

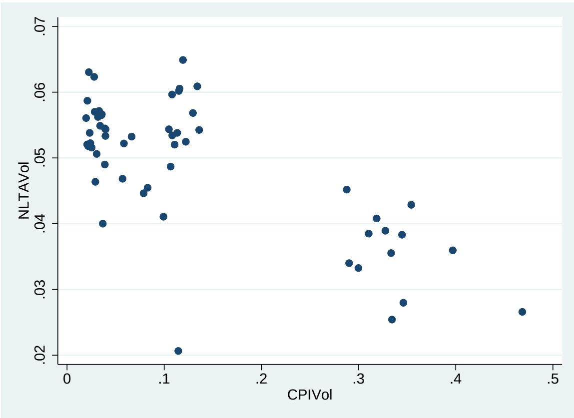
Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



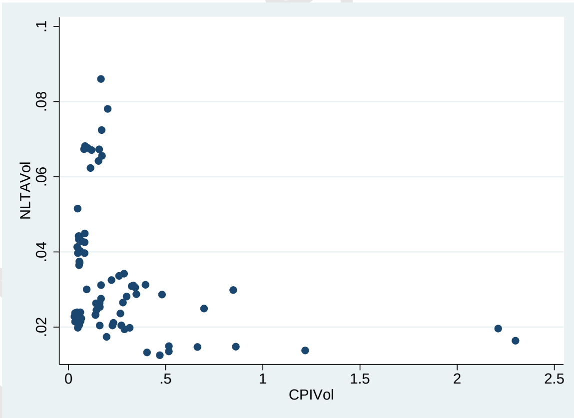

(a) NLTA Volatility *vs* Inflation Uncertainty (full sample)



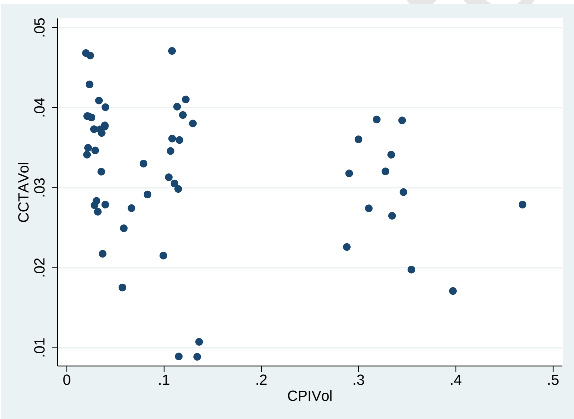

(b) CCTA Volatility *vs* Inflation Uncertainty (full sample)



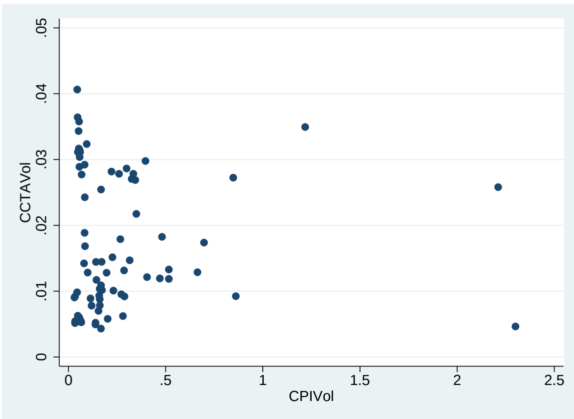

(c) NLTA Volatility *vs* Inflation Uncertainty (EU)




(d) NLTA Volatility *vs* Inflation Uncertainty (non-EU)




(e) CCTA Volatility *vs* Inflation Uncertainty (EU)




(f) CCTA Volatility *vs* Inflation Uncertainty (non-EU)

Figure 1: Cross-sectional Dispersion of Net Loans-to-Total-Assets Ratio and Corporate and Commercial Loans-to-Total-Assets Ratio *versus* Inflation Uncertainty for full data (a-b) and EU and non-EU countries (c-f)

**Highlights**

- Inflation volatility distorts the allocation bank loans.
- Bank managers behave conservatively when inflation volatility is high.
- Analyze a large panel of commercial bank data from 15 countries.
- Observations hold true for the full data, EU and non-EU country groups.