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Determinants of Household Sector Vulnerability in Jamaica: An Application of an ARDL Model and Stress Testing Scenarios

Ahmad Tijani
Financial Stability Department[1][2]
Bank of Jamaica
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Abstract

The recent global financial crisis highlighted the major impact of shocks to the household sector which significantly contributed to systemic risk. In Jamaica, the household sector represents deposit taking institutions' (DTIs') largest credit exposure, accounting for approximately 53.3 per cent of their loan portfolio. Against this background, this paper aims to determine the main factors which affect households' financial vulnerability. The paper employs the Life Cycle Model, which is used to examine household behaviour, in order to identify the factors that affect household financial vulnerability. This model points to the level of household debt, income, inflation and unemployment as being significant factors that affect household financial vulnerability. Additionally, given Jamaica's status as a small open economy, the impact of weather patterns and remittances were also tested. The Auto Regressive Distributed Lag estimation technique was used to measure these effects. The results confirmed that the factors suggested by the Life Cycle Model generally have a significant long run relationship with the assessed household sector financial vulnerability measures. The paper also highlights the sensitivity of household's fragility to positive shocks to the interest rate. Furthermore, the results of the paper confirmed the need for continued focus by policymakers on macroeconomic stability and investment in infrastructure in order to facilitate household recovery from weather irregularities largely resulting from climate change.

JEL Classification Numbers: *C22, D14, E44, G21*

[1] The views expressed are those of the author and do not necessarily reflect those of Bank of Jamaica.
[2] This document is a draft and is representative of ongoing work.

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1. Introduction

In more recent literature on household studies, financial vulnerability has emerged as an area of particular focus for macro-prudential authorities. This is against the background where the global financial crisis in 2008 has demonstrated that rapid expansion in household debt can lead to systemic risk. Financial vulnerability is defined as the ability of a household to recover from discontinuous shocks to either side of their balance sheet. These shocks are typically categorized as either a natural disaster or an economic shock. Economic shocks may include factors such as rising unemployment and general increases in prices while natural disaster shocks could be events such as hurricanes or flooding.[3] Furthermore, while debt is not, by itself, a cause of financial vulnerability, it becomes a threat insofar as this debt is unsustainable. Over the past decade Jamaica has seen steady increases in aggregated household sector indebtedness as measured by the ratio of household sector debt to disposable income. This ratio grew substantially to 58.1 per cent at end-2018 relative to 38.0 per cent recorded in March 2009 (see **Figure 2** in Appendix).

Additionally, risks to the financial system from this vulnerability is of concern given the level of exposure of the banking system to the household sector. Of note, at the end of 2018, the household sector represented deposit taking institutions' (DTIs') largest credit exposure, accounting for approximately 53.3 per cent of their loan portfolio.[4] Given the significance of this credit exposure, any disruption to households' ability to service their loans may have significant ramifications for the financial sector. According to Büyükkarabacak and Valev (2010), household debt is also more precarious for the financial system as this form of debt is not associated with an increase in income in the long run. As a result, rapid expansion of household credit can create conditions that precipitate a financial crisis.

This paper aims to analyze the trends in household financial vulnerability in Jamaica, with a view to identifying the sources of the risks in order to properly assess the existing and impending

[3] According to an IDB report more than half the Jamaican population reside within a mile of the shoreline, increasing the expected occurrences of household damage, and the spread of waterborne illnesses in the event of flooding. These factors are expected to have an adverse effect on the financial vulnerability of households. Also, in the presence of highly leveraged households, the incidences of natural disasters can put an even greater strain on the household sector and lead to an increase in arrears and eventually default on loans.

[4] This figure compares to 36.7 per cent at end December 2002.

threats to the stability of the financial system. Empirical work in this area is relatively new and has been virtually uninvestigated in Jamaica. This paper will also serve to strengthen our understanding of how different aspects of the economy feed into the financial system and can create unforeseen risks. The remainder of this paper is organized as follows: Section 2 will examine the existing literature on household sector vulnerability. Section 3 expatiates the theoretical framework based on the Life Cycle Model. Section 4 presents the data and describes the econometric methodology. The findings of the research are discussed in section 5 and stress scenarios are explored in section 6. Section 7 will conclude and outline the policy implications of the findings.

2. Literature Review

In the empirical literature on household sector financial vulnerability, authors have mainly used three proxies to measure the level of vulnerability. These measures include: debt servicing ratio, which is defined as the amount paid out by household in the servicing of their debt relative to their income; non-performing loans, which captures the buildup of vulnerabilities throughout the financial system and financial margins, which refer to the difference between household income and household expenditure.

Furthermore, studies conducted on household vulnerability generally utilizes two main data sources, which are micro and macro household sector level data, depending on the level of data availability within a country. However, most authors agree that while macro analysis can indicate buildup of risk in the system, understanding financial vulnerabilities at a micro level is important. In other words, macro level household data cannot indicate the specific sources of these threats and does not account for the heterogeneity among households in their reaction to financial shocks. For example, an affluent household may consume its assets in response to a fall in income whereas a poorer household may not have that option. This information is vital to policy decisions. However, few countries maintain micro-level household financial data, mainly due to the high associated costs.

In particular, Mahabir et.al (2014) used financial margins to measure the financial vulnerability of households. They used data from the 2008/2009 Household Budgetary Survey in Trinidad and

Tobago to assess the threats posed to the financial system from shocks to the household sector. They used a probit model to assess the characteristics of a financially vulnerable household which they found to be most dependent on employment, educational attainment and gender. They then used shocks to interest rates, inflation and unemployment to assess the resilience of households and found that households were most susceptible to shocks to the rate of unemployment. The study represents the first micro level assessment of household vulnerability in Trinidad and indeed the Caribbean.

Additionally, Fuenzalida and Ruiz-Tagle (2010) measured financial vulnerability in Chile by way of debt at risk, which they defined as comprising the level of debt servicing as well as the level of expenditure relative to income. They used household survey data to compute the probability of job loss and then utilized Monte Carlo simulations to assess the effects on debt at risk of higher levels of unemployment. They found that the unemployment rate had a positive relationship with debt at risk.

Similarly, Albacete and Lindner (2013) also made use of an extensive household survey conducted in Austria to identify financially vulnerable households and then analyze the potential risks to the financial system emanating from these households. The authors used a threshold value for the debt servicing ratio as well as the debt to assets ratio to define vulnerable households and were able to conclude that, despite the high level of debt, the risks were minimal due to several factors which includes the fact that most vulnerable household have positive net wealth. On the other hand, in Italy, Anderloni et al (2011) used survey data to create a new definition of household financial vulnerability by using responses to specific questions and synthesizing them by way of the Nonlinear Principal Components Analysis methodology. The findings indicated that debt servicing had a positive and robust relationship with vulnerability and this effect was stronger for unsecured debt.

Rinaldi and Sanchis-Arellano (2006) measured vulnerability using non-performing loans (NPLs) in a study in the euro area using macro level data as well. They made use of a life cycle model to derive the theoretical determinants of the probability of default and then used the Fully Modified Ordinary Least Squares (FMOLS) technique to empirically test the determinants of NPLs. They found that the factors included, such as indebtedness, explained a fair proportion of variations in household arrears.

Another such study which used macro-level household data is Abid and Mohd Shafiai (2018), who used macro indicators to determine the influences on household vulnerability in Malaysia, for which they used NPLs as a proxy for this variable. Additionally, they utilized national surveys to extract micro inferences. In addition, an Autoregressive Distributed Lag (ARDL) model was utilized and it was found that prices and unemployment had a long run positive effect on household vulnerability. Further analysis also showed that this result is true for lower income households.

Additionally, Clarke and Wallsten (2003) found evidence, from their analysis of Hurricane Gilbert in Jamaica, to suggest that remittances act as a form of insurance by households. Their findings suggest that households take an active role in determining the amount of remittance they receive. In fact Connell and Conway (2000) assert that households respond to financial difficulties by requesting funding from their remitters. Although this analysis was done in the context of natural disasters, it does not take much imagination to see how remittances could be used as a source of insurance in the case of other financial difficulties. If this hypothesis is true, then we should expect a negative relationship between remittances and our measures of household vulnerability as households would request more funding from remitters during times of financial stress, thereby reducing their vulnerability.

Currently, micro-level household level data is not used to assess household sector vulnerability in Jamaica due to data unavailability. Therefore, this paper will follow the methodology of Abid and Mohd Shafiai (2018) in using macro level data.

3. Theoretical Framework

From the theoretical literature, household borrowing can be explained by demand side factors. Drawing from the Life Cycle Model of Modigliani, we can model the intertemporal consumption decisions of a representative household as such:

$$V(C_1, C_2) = U(C_1) + \frac{1}{1+\beta} E[U(C_1)] \tag{1}$$

Where C_i is the i[th] period consumption decision; β is the subjective rate of time preference and $E(.)$ is the expectation operator, conditional on information available in period one. Furthermore, U is the constant relative risk aversion (CRRA) utility function characterized by $U' > 0$, $U'' < 0$ and $U'(0) = \infty$. In the second period consumption and income are uncertain. Income is assumed to follow a stochastic process: with probability q period 2 income is equal to Y_L, a low level of total income, while with probability $(1-q)$ period 2 income equals Y_H, a high level of income. Now, assuming that there exists a perfect capital market, households will be able lend and borrow at the risk free rate R. The intertemporal consumption decision then becomes

$$V(x_1, x_2) = U(Y_1 + x_1) + \frac{1}{1+\beta}\left[qU(Y_L + x_2) + (1-q)U(Y_H + x_2)\right] \tag{2}$$

where households now choose how much to save or borrow and $x_1 > 0$ and $x_2 < 0$ for borrowers and $x_1 < 0$ and $x_2 > 0$ for savers.

The budget constraint for households is

$$x_2 = -(1+R)x_1 \tag{3}$$

At optimum, the MRS equates to $(1+R)$, where

$$MRS = \frac{U'(Y_1 + x_1)(1+\beta)}{[q\,U'(Y_L + x_2) + (1-q)U'(Y_H + x_2)]} = 1+R \tag{4}$$

Lenders will only be willing to lend freely at the risk free rate, R, if credit markets are perfect, meaning there is no risk of default. However, due to bankruptcy and insolvency laws, there exists a real credit risk for lenders. Assuming that borrowers will be unable to repay the loan in the bad state, which occurs with probability q, lenders will charge a higher rate than the risk free rate. In a competitive market, lenders will charge a rate such that their expected profits are zero.

$$1 + r = \frac{(1+R)}{(1-q)} \tag{5}$$

Lenders will now be willing to lend at $1+r$ up to the maximum loan size, b_{max}, which a borrower can afford to repay if they receive Y_H in period 2, where

$$b_{max} = \frac{1}{1+r}(Y_H - Y_L) \tag{6}$$

The model is augmented by adding the inflow of remittances which is a significant source of income in developing countries, especially in Jamaica. The size of the inflow of remittances is viewed as being countercyclical and remittances are expected to be higher in the low income state of the world.[5] In addition, a probability component, α, is added to the model to represent the probability that remittances will be high in the low income state of the world, in which case the borrower would be able to repay the loan. In case of default, the lender can claim income greater than Y_L and remittances above T_2.

Accounting for the possibility of default with bankruptcy laws, as well as the added remittances component, the utility function becomes.

$$V(x_1, x_2) = U(Y_1 + x_1) + \frac{1}{1+\beta}[(1-\alpha)qU(Y_L + T_2) + \alpha qU(Y_L + T_1 + x_2) + (1-q)U(Y_H + T_2 + x_2)] \tag{7}$$

Such that

$$T_1 > T_2 \tag{8}$$

And the budget constraint becomes

$$x_2 = -(1+r)x_1 \tag{9}$$

Assuming optimization, the borrower's MRS is

[5] Henry, Moulton & Ricketts (2009) found evidence in Jamaica of rises in remittances during periods of natural disasters. This is further corroborated by evidence from the World Bank and IDB finding that remittances in developing countries like Jamaica tend to be stable and countercyclical during growth slowdowns in the recipient country(Maimbo and Ratha, 2005; Orozco, 2009; Todoroki, Vaccani & Noor, 2009)

$$MRS_B = \frac{U'(Y_1 + x_1)(1+\beta)}{[\alpha q U(Y_L + T_1 + x_2) + (1-q)U'(Y_H + T_2 + x_2)]} = 1 + r \tag{10}$$

Extracting the probability of default from the above equation yields the following

$$q = \frac{(1+r)U'(Y_H + T_2 + x_2) - (1+\beta)U'(Y_1 + x_1)}{(1+r)U'(Y_H + T_2 + x_2) - \alpha U'(Y_L + T_1 + x_2)} \tag{11}$$

From this framework, we can determine the factors which influence the probability of default, which we assume to be related to the likelihood of a loan falling into arrears. These factors are: the amount borrowed, x_1, current income, Y_1, and the level of remittances, T_2 & T_1. In addition, the probability of default would also be affected by the lending rate, r, and future income and wealth which is itself dependent on the rate of unemployment and the development of asset prices. Arrears would further depend on the time preference, β, which is related to the future expectations about inflation. For the purpose of this study, NPLs to Total loans, debt servicing ratio and debt to income are used to measure the probability of a loan falling into arrears

4. Methodology and Data

Based on the implications of the theoretical framework in section 3, the following model is developed and comprised quarterly data spanning the period 2003Q2 to 2018Q4:

$$FV_t = \alpha_1 + \beta_1 \, Debt_t + \beta_2 GDP_t + \beta_3 \, Unempl_t + \beta_4 \, Infl_t + \beta_5 \, Int_t + \beta_6 \, Rain_t + \beta_7 \, Rem_t + \beta_8 \, REPI_t + \varepsilon \tag{12}$$

Where FV refers to the indicator of Household Financial Vulnerability as measured by the ratio of NPLs and Debt to Income; Debt refers to the log of total household debt; GDP refers to the log of Real GDP; Unempl refers to the rate of unemployment, Infl refers to the 12-month point-to-point inflation rate; Interest refers to the weighted average lending rate for DTIs, Rainfall refers to the log of the average rainfall across the island, Rem reflects the log of the net flow of remittances in Jamaican Dollars; REPI refers to the Real Estate Price Index and ε is the error term (see **Table 7** in Appendix for details of variable selection).

The estimation technique applied will be that of the autoregressive distributed lag (ARDL). This model deals with single cointegration and is introduced originally by Pesaran and Shin (1997) and further extended by Pesaran et al. (2001). The ARDL approach has the advantage of not requiring all variables to be I (1) and is still applicable if there are I (0) and I (1) variables the data set employed. Another advantage of this approach is that the model utilizes a sufficient number of lags to capture the data generating process in a general-to-specific modelling framework (Laurenceson and Chai, 2003). The ARDL model also allows for different optimal lags among the selected variables, which is not possible in more conventional cointegration procedures. Furthermore, the ARDL procedure allows for cointegration even in the presence of endogenous variables; moreover, the endogeneity bias tends to be very small and irrelevant (Inder, 1993). The Error Correction Model (ECM) also integrates the short-run dynamics with the long-run equilibrium without losing long-run information. Therefore, given the equation outlined above, the following relationships can be specified:

$$\begin{aligned}\Delta FV_t = \alpha_1 &+ \beta_1 FV_{t-1} + \beta_2 Debt_{t-1} + \beta_3 GDP_{t-1} + \beta_4 Unempl_{t-1} + \beta_5 Infl_{t-1} \\ &+ \beta_6 Int_{t-1} + \beta_7 Rain_{t-1} + \beta_8 Rem_{t-1} + \beta_9 REPI_{t-1} \\ &+ \sum_{i=1}^{n} \gamma_1 \Delta FV_{t-i} + \sum_{i=1}^{n} \gamma_2 \Delta Debt_{t-i} + \sum_{i=1}^{n} \gamma_3 \Delta GDP_{t-i} \\ &+ \sum_{i=1}^{n} \gamma_4 \Delta Unempl_{t-i} + \sum_{i=1}^{n} \gamma_5 \Delta Infl_{t-i} + \sum_{i=1}^{n} \gamma_6 \Delta Int_{t-i} \\ &+ \sum_{i=1}^{n} \gamma_7 \Delta Rain_{t-i} + \sum_{i=1}^{n} \gamma_8 \Delta Rem_{t-i} + \sum_{i=1}^{n} \gamma_9 \Delta REPI_{t-i} + \varepsilon\end{aligned} \tag{13}$$

Where Δ represents the first difference operator and n is the optimal lag length. Also, γ represents the short- run dynamics of the model whereas β gives the long run relationship, if one exists. The optimal lag is determined using the Schwarz Bayesian Information Criterion (SBC). Thereafter we estimate the Error Correction Model (ECM), given as

$$\sum FV_t = \sum_{i=1}^{n} \gamma_1 FV_{t-i} + \sum_{i=1}^{n} \gamma_2 Debt_{t-i} + \sum_{i=1}^{n} \gamma_3 GDP_{t-i} + \sum_{i=1}^{n} \gamma_4 Unempl_{t-i} + \sum_{i=1}^{n} \gamma_5 Infl_{t-i} + \sum_{i=1}^{n} \gamma_6 Int_{t-i} + \sum_{i=1}^{n} \gamma_7 Rain_{t-i} + \sum_{i=1}^{n} \gamma_8 Rem_{t-i} + \sum_{i=1}^{n} \gamma_9 REPI_{t-i} + \mu ECT_{t-1} + \varepsilon_t \tag{14}$$

Where ECT represents the error correction term and μ is the speed of convergence. This variable must be significant and have a negative value for a long run relationship to be present and meaningful.

After the estimation of this model, further analysis will be done using a quasi-stress test based on macro data and insights from the empirical findings.

5. Results of the Study

The selected variables were initially tested for stationarity using the Augmented Dickey-Fuller (ADF) test. This test was conducted to ensure that none of the variables were integrated of order 2 or higher, as the results from the ARDL model would be unreliable in the presence of such variables. The results find that this requirement is met (See **Table 8** in Appendix).

The next step is to test for cointegration to determine whether a long-term relationship exists among the variables which we examined by estimating equation (13). As stated in Section 4, the SBC was used to determine the optimal order of lags with a maximum lag order of eight imposed on the dependent variable, and four on the regressors. In addition, the bounds testing approach, which is similar to a Wald test (F-test), was used to examine the long run coefficients in equation (13), assuming that the other variables are exogenous. The null hypothesis is that $\beta_1 = \ldots = \beta_9 = 0$. The critical values for the bounds test can be found in Pesaran and Shin (1996) and Pesaran et al (2001) which provides an upper and lower bound value. The test statistic being less than the lower critical bound means we are unable to reject the null hypothesis of no cointegration among the underlying variables. If the test statistic is greater than the upper bound then the null hypothesis is rejected, indicating that there is cointegration. A value lying in between the upper and lower bound infers inconclusive results.

As can be seen in **Table 1**, the coefficients of the bounds tests were high enough to reject the null hypothesis of there being no long run relationship at the 1% level of significance for both models. We can further verify this result by estimating equation (14) and evaluating the error correction term. Subsequently, the results reveal that the error correction term is negative and

Table 1: Bounds Test

H_0: No cointegration	*Test statistic*	*5% Critical Bounds*		*1% Critical Bounds*	
		I(0)	I(1)	I(0)	I(1)
FV=NPL	5.52	2.22	3.39	2.79	4.1
FV=D-T-I	7.99	2.55	3.68	3.15	4.43

Table 2: Long run estimates

highly significant which confirms the existence of cointegration (See **Table 2**).

The models were estimated with a drift component and a trend component was added to the second model. In addition, a dummy variable was included to account for a structural break for the 2008 Global Financial Crisis in Model 1.

The regressand = NPL, D-T-I		
Regressor	**NPL**	**D-T-I**
Debt	6.67***	1.87***
GDP	-20.30***	15.01***
Unempl	-0.08	0.16**
Infl	-0.33***	0.42***
Int	0.17***	0.23***
Rem	-5.90***	-3.05**
Rain	-2.47***	-0.10
REPI	0.02**	-0.04***
GFC	1.64***	---
Constant	265.94***	-190.91***
Trend	---	0.47***
Error Correction Term	-1.17***	-0.82***
Log Likelihood	64.07	80.25
Durbin Watson	2.51	2.11

Where * represents significance at the 10% level. ** represents significance at the 5% level. *** represents significance at the 1% level

Model 1 – FV=NPL

From the results of model 1, Debt and the interest rate were found to have a positive and significant long run relationship with the ratio of NPLs, which is consistent with our a priori expectations. This result implies that the ratio of NPLs, as an indicator of household financial vulnerability in Jamaica, is sensitive to the size and cost of credit within the market.

A measure of weather disturbances was included in the model and is proxied by inches of rainfall. The expectation was that an increase in rainfall would impose additional costs upon households and increase their vulnerability. The results indicate that rainfall has a significant long run relationship with household financial vulnerabilities, however the relationship is found to be negative. This result can possibly be explained by the deleterious effect of water shortages on household finances during times of drought. These conditions usually impose severe costs upon households and therefore an increase in rainfall during these periods can have a beneficial effect on household financial vulnerability.

Remittances and GDP were found to have a significant, negative long run relationship with the ratio of NPLs. This result aligns well with previous evidence in Jamaica which pointed to a countercyclical relationship for remittances as well as the evidence stating remittances acts as insurance for households.[6] GDP was also expected to have a negative relationship with household financial vulnerability as it is used to proxy household income.

However, unemployment was not found to have a significant long run relationship with the ratio of NPLs. Furthermore, the coefficient for the relationship was negative. In order to explain this result, the direction of causality was tested via the Granger causality test, which found that, at a 5% level of significance, the ratio of NPLs granger causes unemployment. This could be related to the impact of remittances which also acts as a substitute to employment for persons, particularly those who are marginally employed. An increase in remittances is predicted to reduce the ratio of NPLs and, as an indirect effect, may cause some underemployed persons or persons earning very low wages to forego employment for the remittances they receive. This would increase the rate of unemployment. This effect may explain the weak, negative relationship between unemployment and the ratio of NPLs.

In addition, inflation had a significant, negative long run relationship with the ratio of NPLs. Higher, but moderate, inflation can lead to better conditions for households with fixed rate obligations. In this case, an increase in the rate of inflation will cause household financial vulnerability to fall. Another explanation for this result could be the relationship between inflation and GDP. Higher inflation is associated with higher GDP in the long run. Therefore an increase in inflation will have a positive effect on GDP in the long run and as such a negative effect on household financial vulnerability.

Conversely, the residential real estate price index (REPI) was positively related with the ratio of NPLs in the long run. This implies that for a significant proportion of households, the increasing of real estate prices serves to increase their financial vulnerability. This may be due to many households renting their homes rather than owning them, in which case real estate serves as a

[6] See references in Section 2 and 3

liability rather than an asset. In such case, an increase in real estate prices would negatively affect their balance sheets and thereby increase their chances of falling into arrears. Finally, it was found that the GFC had a significant effect on the ratio of NPLs, shifting the variable up by 1.64 per cent.

The Error Correction Term, though negative and highly significant, exceeded 1 in absolute value. This implies a rapid speed of adjustment in which short term deviations are corrected in less than a quarter.

Model 2 – FV=D-T-I

Model 2 used Debt to Income as the measure of household financial vulnerability, the results showed a positive and significant long run relationship with size and cost of credit. This proves to be a commonality between both models. However, in contrast to the Model 1, GDP had a positive relationship with debt to income. This could be largely due to the fact that, with economic growth, it would be possible for households to take on loans at lower costs and reduce the ratio of NPLs. Similar to Model 1, remittances was found to have a negative long run relationship with debt to income. The implication of this result is two-fold. Firstly, remittances are counter-cyclical in nature and would increase during downswings in the economic cycle which correlates with credit crunches. Additionally, in such case, remittances can act as an alternative source of funds for households.

Unemployment was found to have a significant positive long run relationship, which is consistent with a priori expectations. In particular, as unemployment increases, it is expected that income will decline and consequently raise debt to income levels. Likewise, inflation has a positive long run relationship with debt to income. While the REPI has a negative long run relationship, implying that households are dissuaded from taking on mortgages as housing prices rise. This is especially likely given that the REPI accounts for NHT housing, which largely caters to the lower end of the housing market.

The model carried a negative and significant error correction term which helps to confirm the bounds tests conclusion of cointegration among the variables. The coefficient of the variable is -0.82, implying that 82 per cent of any short term fluctuations is corrected within a quarter.

Post Estimation Tests

To verify the credibility of our results, a series of post estimation tests were conducted. As such, the diagnostic tests examined were a test for serial correlation, stability, normality as well as heteroscedasticity.[7] The presence of serial correlation in a model will produce unbiased and consistent estimators, however, the standard errors will be either understated in the case of positive serial correlation, or overstated in the case of negative serial correlation. The models have a Durbin-Watson test statistic of 2.5 and 2.1, respectively. However, the Breusch-Godfrey Serial Correlation LM test, which fails to rejects the null hypothesis of no serial correlation, and an examination of the correlogram of squared residuals confirm the veracity of the models.

The models are tested for heteroscedasticity using the Breusch-Pagan-Godfrey test which fails to reject the null hypothesis of homoscedasticity. The models are also tested for stability using the CUSUM and CUSUM of squares. Observing the graphs, we can see that the models remain within the 5 per cent bounds for both the CUSUM and CUSUM of squares and we can therefore confirm stability.

6. Stress Testing Households

This section examines stress testing of the household sector by applying hypothetical but plausible shocks to three indicators of household financial vulnerability, namely: the household debt service ratio (DSR), households' net financial position (HNFP) as well as the debt to income indicator. This sensitivity analysis will hopefully speak to the short-run risks posed to the system from possible fallouts in key variables, using these indicators as measures of financial fragility. As stated in section 2, DSR is a commonly used measure of financial vulnerability, but was not used in the empirical analysis due to there not being a sufficiently long time series for the indicator in Jamaica. Households' net financial position (HNFP) is defined as the difference between the aggregated values of household financial assets (HFA) and household financial liabilities (HFL) and will serve as a macro based equivalent for financial margins.[8] As for the

[7] Graphs and tables reported in Appendix

[8] Household Financial Assets comprises the value of Pensions, Deposits in DTIs, Retail Repos, Life assurance and annuity contracts and Policyholders' funds on deposit. Household Financial Liabilities comprises overall debt outstanding from personal loans for DTIs and the residential mortgage loans outstanding for NHT.

household debt servicing ratio (DSR), an aggregated figure is arrived at using the methodology of Drehmann et al (2015). The formulation of the DSR consists of DTIs' weighted average interest rate, household debt, the average remaining maturity of the outstanding debt stock and personal disposable income.[9]

Stress Testing Assessment:

For the stress tests, there was an evaluation of the three indicators discussed above as at end-December 2018. Three shocks were considered in particular, a rise in interest rates, a fall in remittances and an increase in household debt. The effect on these indicators from each shock was individually assessed as well as the combined impact.

These shocks affect the indicators in a number of ways. More specifically, a rise in interest rates affects the DSR positively. A fall in remittances affects the personal disposable income which affects the DSR and Debt to Income indicators. An increase in household debt will lead to a deterioration in all three indicators.

Interest rate increases: Interest rate increases of 300, 400 and 600 bps were considered. We use the rapid increase in interest rates experienced in the first 9 months of 2003 as our reference, where the variable rose by 500 bps.[10] These interest rate shocks in turn affect the DSR.

Remittances decrease: Negative shocks of 10, 12 and 15 per cent were applied to the level of remittances. We use the GFC as our point of reference, where the USD value of net remittances fell by 24.9% in March 2009, but the JMD equivalent only fell by 11.4% due to a simultaneous large depreciation in the local currency. This shock will feed into our measure of Personal Disposable Income, which will thereby affect the DSR and Debt to Income levels.

Increase in household debt: Between December 2016 and December 2017, there was an expansion in household credit of 17.7%. As such, we consider shocks of 10, 15 and 20 per cent to household debt. This shock affects all three indicators being examined directly.

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[9] The DSR for households is computed as follows: $\boldsymbol{DSR_{j,t}} = \frac{i_{j,t}}{(1-(1+i_{j,t})^{-s_{j,t}})} * \frac{D_{j,t}}{Y_{j,t}}$ where $D_{j,t}$ denotes the total stock of household debt, $Y_{j,t}$ denotes aggregate income available for debt service payments, $i_{t.j}$ denotes average interest rate on the existing stock of debt and $s_{j,t}$ the average remaining maturity across the stock of debt.

[10] The average weighted lending rate was the applicable interest rate used. Additionally, we include a shock of 600 bps to account for the low inflation level currently which may rise in the case of a crisis and put further upward pressure on the interest rates.

Several scenarios were examined in a low, medium and high stress environment defined below (see **Table 3**). The shocks chosen were guided by historical events and there is a focus on extreme shocks which may not be likely but are plausible enough given past scenarios.

Table 3: Stress Scenarios

	Interest rate	Remittances	Household Debt
Reference point	+500 bps	-11.4%	+17.7%
Low	+300 bps	-10%	+10%
Medium	+400 bps	-12%	+15%
High	+600 bps	-15%	+20%

Stress Testing Results

In analyzing the results, we use a threshold of 3 standard deviations to signify overbearing risk. Using this methodology, the threshold for the DSR is 9.63 per cent; for HNFP, the threshold is 19.98 per cent; and for Debt to Income, the threshold is 74.35 per cent. The stress tests are carried out individually first (See **Table 4**). The results indicate that the DSR is most sensitive to shocks to the liability side of a household's balance sheet as seen in the large effects from shocks to the interest rate and increases in the debt level, with a high shock to the interest rate being enough to breach its 3 standard deviation threshold. Comparatively, a shock to the income level through a fall in remittances or compensation from abroad had a more subdued impact. As for HNFP, a high shock to the level of debt would not be enough to bring the figure to its threshold value, ceteris paribus, implying some level of resilience in the indicator. With regards to Debt to Income, while most sensitive to shocks to the debt level, would remain resilient to each of the individual shocks.

Table 4: Individual Stress Scenarios

	Original	Low Int	High Int	Low Rem	High Rem	Low Comp	High Comp	Low Debt	High Debt
DSR	7.17	8.84	10.52	7.36	7.46	7.19	7.21	7.88	8.60
ppt change	0.00	1.67	3.35	0.19	0.29	0.02	0.04	0.71	1.43
HNFP/GDP	32.98	32.98	32.98	32.98	32.98	32.98	32.98	30.07	27.17
ppt change	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-2.91	-5.81

Debt to Income	55.93	55.93	55.93	57.41	58.18	56.09	56.26	61.52	67.11
ppt change	0.00	0.00	0.00	1.48	2.25	0.16	0.33	5.59	11.18

In addition, three aggregated scenarios were examined (See **Table 5**). The results show the sensitivity of the DSR to our catalogue of shocks, with the combination of low level shocks being enough to send the indicator over the threshold, while the other indicators would remain resilient to even a combination of high level shocks.

Table 5: Aggregated Stress Scenarios

	Original	Low	Med	High
DSR	7.17	9.89	11.20	13.11
% change	0.00	37.95	56.31	82.96
HNFP/GDP	32.98	30.07	28.62	27.17
% change	0.00	-8.81	-13.22	-17.62
Debt to Income	55.93	62.51	66.62	69.69
% change	0.00	11.78	19.12	24.61

The noted sensitivity of the DSR points to this indicator being more responsive to changes in the economy than its counterparts due to its consideration of changes in the interest rates within the economy. It is likely that the notable expansion of household credit in recent years as indicated in the debt to income and HNFP indicators has been facilitated by the fall in interest rates over the same time. The DSR does the best job of capturing the risks posed by a change in the trend for interest rates directly, which would be missed by these other indicators, and as such is a better indicator of risks to the financial system.

7. Conclusion and Policy Implications

Household financial vulnerability is an important issue for policymakers given the recent global financial crisis. However, research in this area has been sparse, mainly due to the lack of granular data. Within this context, this paper has sought to understand the determinants of household financial vulnerability in Jamaica making use of macro-level data and a combination of ARDL modelling and quasi-stress testing scenarios. The study, from its usage of multiple measures of household financial fragility, is able to highlight the subtle differences in the information they each carry. It is important to use these indicators complementarily for this reason. However, the volume and cost of credit to household were found to both be associated with a deterioration in both measures of financial vulnerability. Also gleaned from the study was the role remittances played in impacting household resilience. Furthermore, the study also highlights the threats from changing climates which is predicted to cause more severe and long-lasting drought patterns which may prove problematic for household's resilience. The study also found that the most influential contributor to household financial resilience, is expansion of income.

Through the use of quasi-stress testing, the paper was able to assess the short term risk implications to Jamaica's financial system from plausible shocks from key variables as pointed to by the results of our regression analysis. The results indicate that there are threats to the system's stability, particularly from a reversing of current trends of falling interest rates. With falling public debt, and increasingly accommodative rates by the Bank of Jamaica, interest rates have trended downwards, and the household financial vulnerability indicators would deteriorate significantly in the case of a positive shock to interest rates.

This result is indicative of the need for continued focus of the government on improved efforts to stimulate economic growth. The government needs to ensure the efforts to reduce its footprints in the debt market is sustained, as the fallout from reversing interest rates decline can be detrimental to the financial position of households and, as a result of the large exposure, the wider financial system. Additionally, stronger focus on improved economic growth should also be coupled with increased infrastructural development, improved financial literacy and other financial inclusion strategies. Initiatives of this nature can aid in ensuring that households are resilient to large downswings which may pose severe systemic risks to the financial system and by extension the wider economy.

The paper was limited in its analysis due to limitations of the data available in Jamaica. An imperative policy consideration going forward is the need for more granular and comprehensive data on the household debt factors at play within the Jamaican economy. Without more accurate and complete data, it is possible for policy makers to be unaware of risks being posed to the financial system and undermine The Bank of Jamaica's mandate in ensuring financial system stability. It is also possible that the risks may be overstated, leading to inappropriately stringent policy decisions, which could curtail the relatively small growth which the economy has been experiencing recently. The form of data which would be appropriate for proper analysis of the issue would be household surveys as they are able to properly capture the true extent of the debt burden faced by households and the specific sources of this debt. While the main concern of The Bank of Jamaica is on the risks posed to the regulated financial system by those indebted to banks, it is easy to imagine that these risks will be augmented by factors outside the financial system. As such, it would be useful to understand the extent to which the household is leveraged to entities outside the formal financial system as well as a more accurate representation of their income and holdings of assets which they may draw on to repay debt as they mature.[11]

Future work should look at working with micro data when this data becomes available. There are limitations posed by the use of macro level data. In addition to the inability to identify the specific risks posed by subsections of the economy, there is also an issue with the reliability of the macro dataset due to the specific economic context of small developing nations such as Jamaica. According to a report from the National Financial Inclusion Council of Jamaica, although Jamaica has the highest proportion of adults with a bank account among countries within the middle income classification, these accounts are not actively used.[12] Also, although 74% of Jamaicans had reported setting money aside within the last year for an emergency, only a third did so through a regulated financial institution. Furthermore, the report also indicated that only 11% of households had access to credit from regulated entities, while 45% indicated they had received credit within the past year.

This points to relatively sparse interactions between the regulated financial system and households. As a result, the macro data used from regulated entities, may not give a comprehensive view of the nation's risk profile. It is difficult to say what the specific implications of this data gap may be, because while one might expect that the true extent of the nation's debt burden is understated due to unrecorded debt levels, the measurements of the nation's financial assets and income may also be understated. As such, in order to more

[11] Although it is true that households tend to understate their income on surveys.

[12] 23% of Jamaicans reported not making a withdrawal or deposit within the past year, compared to an average for the region of 11%

accurately assess the sustainability of current debt levels and to quantify and understand the risks which are posed in more detail, more granular and comprehensive data is necessary.

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Appendix

Table 6: Outline of Literature

Author	Abid and Mohd Shafiai (2018)	Rinaldi and Sanchis-Arellano (2006)	Fuenzalida and Ruiz-Tagle (2010)	Mahabir et al (2014)
	Malaysia	Euro-Area	Chile	Trinidad and Tobago
A) HOUSEHOLD FINANCIAL VULNERABILITY	Household Non-Performing Loans	Household Non-Performing Loans to Total Loans	▪ DSR ▪ Financial Margins	Financial Margins
B) INTEREST RATE	Weighted Average lending rate	Real lending rate		
C) INCOME	GDP	Real disposable income per household		
D) FUTURE INCOME	Unemployment	Unemployment and house price index		
E) TIME PREFERENCE	CPI	Inflation		
Variables shocked			Unemployment	Interest Rates Inflation Unemployment
Factors considered				Demographic and socio-economic factors
Estimation Technique	ARDL	Panel FMOLS	Stress Testing	Probit/Stress Testing

Table 7: Variable definition

Variable	Definition	Source
Non-Performing Loans	Past Due loans to households in arrears for over 90 days as a proportion of total household loans for DTIs	Bank of Jamaica
Debt Service Ratio	A formulation of household debt payments as a proportion of income using aggregated, macro-level data	Bank of Jamaica
Household Debt	Personal (non-business) loans to deposit taking institutions and residential mortgages to the National Housing Trust	Bank of Jamaica
Household Debt to Income	Household Debt as a proportion of Personal Disposable Income + Net Remittance Inflow	Bank of Jamaica
Interest Rate	Weighted Average Lending Rate on Instalment Credit, Mortgages and Personal Credit from DTI's	Bank of Jamaica
GDP	Gross Domestic Product	Bank of Jamaica
Unemployment rate	The rate of unemployed persons to persons within the labor force	Bank of Jamaica
Rainfall	The Average quarterly rainfall in inches across the island	The Meteorological Service of Jamaica
Remittances	The net inflow of remittances from abroad	Bank of Jamaica
REPI	The residential real estate pricing index for Jamaica derived from data on NHT housing	Bank of Jamaica
Inflation	The 12 month point to point rate of inflation	Bank of Jamaica

Figure 2: Debt to Income

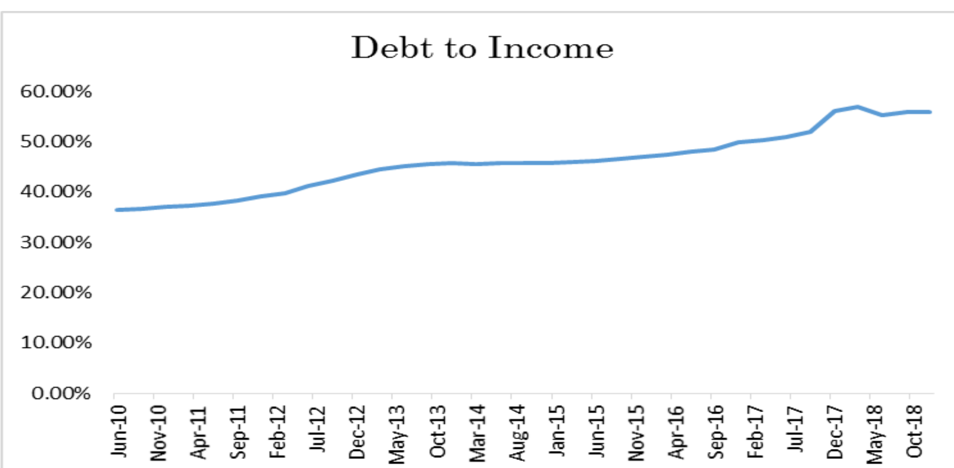


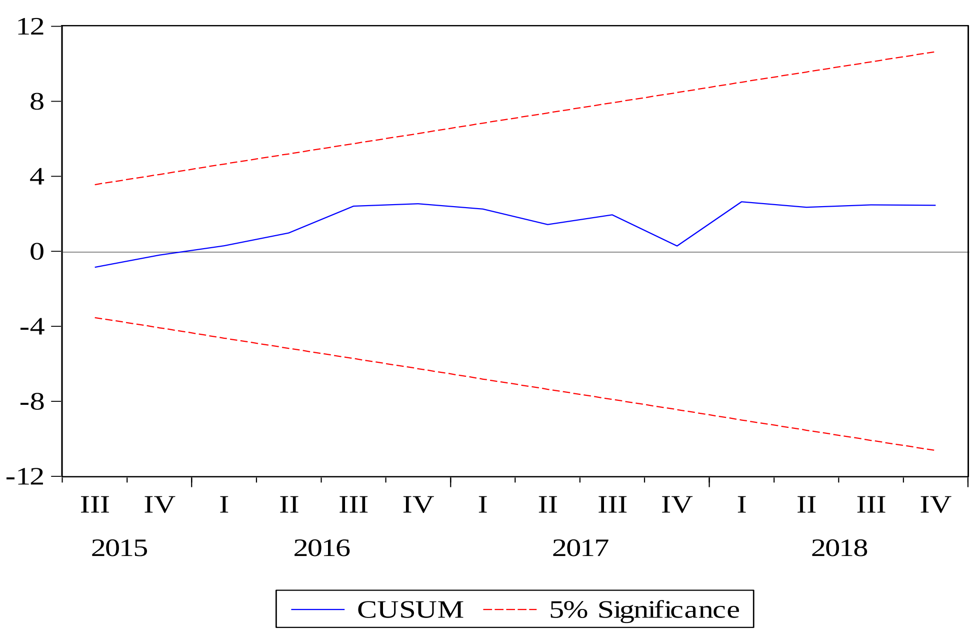
Table 8: Unit Root Tests

Variable	*ADF test-statistic*
NPL	-2.22 (-4.64)***
D-T-I	0.64 (-6.15)***
Debt	-0.05 (-11.99)***
GDP	-0.90 (-7.34)***
Unempl	-2.02 (-10.16)***
Infl	-1.44 (-7.25)***
Int	-1.42 (-14.68)***
Rain	-3.37***
Rem	-1.88 (-3.28)**
REPI	-0.31 (-8.01)***

The ADF tests for the first difference of each variable are shown in parentheses. *** denotes significance at the one per cent level while ** denote significance at the five per cent level using the Fuller (1996) critical values.

Figure 3: CUSUM graph

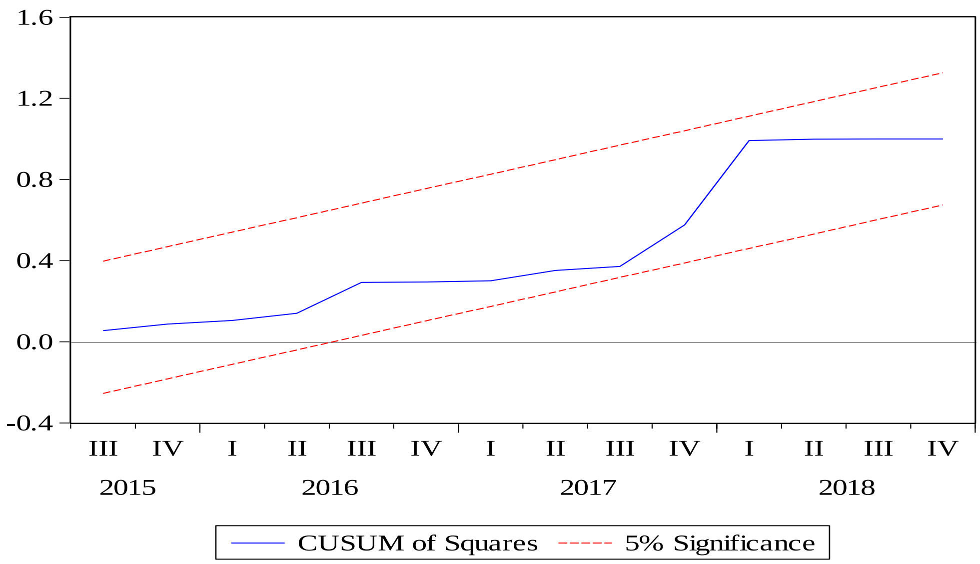
Model 1:



Model 2:

Figure 4: CUSUM of Squared Residuals Graph

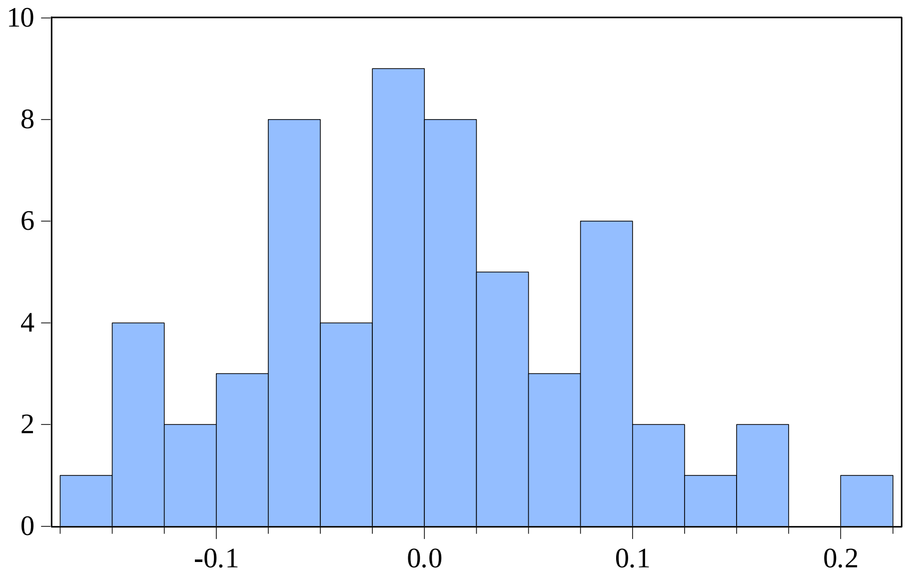
Model 1:



Model 2:

Figure 5: Results of Normality Test

Model 1:



Series: Residuals	
Sample 2004Q2 2018Q4	
Observations 59	
Mean	9.06e-14
Median	-0.002347
Maximum	0.212650
Minimum	-0.159818
Std. Dev.	0.082387
Skewness	0.254516
Kurtosis	2.684732
Jarque-Bera	0.881333
Probability	0.643607

Model 2:

<u>Model 1:</u>

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.020092	Prob. F(2,14)	0.3898
Obs*R-squared	8.573312	Prob. Chi-Square(2)	0.0138

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.844771	Prob. F(42,16)	0.6793
Obs*R-squared	42.85770	Prob. Chi-Square(42)	0.5206
Scaled explained SS	2.032740	Prob. Chi-Square(42)	1.0000

<u>Model 2:</u>