“Three empirical analyses on Financial Literacy, Natural Disasters and Fiscal Multipliers”

TESIS PARA OPTAR AL GRADO DE DOCTOR EN ECONOMÍA

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Introduction

This doctoral dissertation is composed by three research papers elaborated along my doctoral studies in the Department of Economics of the University of Chile. These essays analyze three quite different topics, which, in a way, revels the path I followed during my doctoral work always discovering many areas of interest. But it also shows the common route I chose to explore them by focusing in empirical analysis. Two of the three papers of this thesis are already published in Web of Science (WoS) peer-reviewed journals and the most recent one has already been accepted for publication in a WoS journal (cover pages and acceptance mail for the last paper available in in the Annex). These works are presented here in a reverse chronological order starting from the most recent one.

The first presented paper is entitled "*State Dependence of Fiscal Multipliers in Chile - An Independent Component Approach to Identification*". This paper proposes and implements new estimations of fiscal multipliers for the Chilean economy, updating the methodology previously used in the literature. Motivated by recent research, we implement an independent component analysis into a nonlinear Time-Varying Auto Regressive (TVAR) setting for shock identification. We find that the results of previous studies using a Cholesky decomposition strategy lack robustness when using the updated more agnostic approach. This paper has been accepted for publication in the Latin American Economic Review Journal.

The second research, "*Carbon dioxide atmospheric concentration and hydrometeorological disasters*" was published in the Springer journal *Natural Hazards,* in January 2022. This paper studies the relation between *CO2* concentration and the incidence of hydrometeorological disasters at the global level, and generates projections of this type of natural disasters at country level to year 2040. We use country level panel data to estimate the incidence on disasters at country level. Controlling for country specific factors, we extract from there a global path for such disaster's probability and evaluate its relation to the *CO2* levels in the atmosphere. We find a meaningful relation between the global probability of disasters and the *CO2* levels, which we use to support the already mentioned projections to year 2040 conditional on Shared Socioeconomic Pathways *CO2* scenarios. Finally, we produced the country level probability of hydrometeorological disasters using in-sample average relations between global and country specific incidence of disasters.

The third paper, entitled "*Is financial literacy an economic good?"* was published in the WoS journal *CEPAL Review*, in 2015. This paper studies whether conceptualizing financial literacy as an economic good is consistent with people's behavior toward it. The main idea behind the methodology used is that if that premise holds, then people should be willing to invest more in financial literacy during periods when its value arguable goes up. We used Chilean data from four waves of Chile´s Social Protection Survey (Encuesta de Protección Social), build a measure of financial literacy and tested if it rose around periods when people faced important financial decisions that the data allowed us to identify (i.e. getting married, having a child, first time obtaining a permanent job). We find no evidence supporting the widespread claim.

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I. State Dependence of Fiscal Multipliers in Chile - An Independent Component Approach to Identification[1]

Abstract

In studying the economic cycle dependency of fiscal multipliers in Chile, we implement an independent component analysis for structural shock identification within a non-linear vector autoregressive setting with generalized impulse response functions. Thereby we relax more restrictive assumptions adopted in previous studies, namely the a-priori assumption of a recursive model structure and the use of linear impulse response functions. As a result, we cannot fully confirm core insights from more restrictive structural models: we find no significant differences in neither government spending nor government revenues multipliers when comparing different states of the economy. Moreover, our estimates imply that fiscal multipliers in Chile do not differ significantly from zero.

Key words: Threshold vector autoregressions, generalized impulse response, independent components, fiscal multiplier

JEL Classification: C32, G15

[1] This paper has been accepted for publication in the Latin American Economic Review journal.

1. Introduction

Fiscal policy in general has received significant attention since the Great Recession, as governments have widely implemented fiscal policy packages to fight the economic slump. Whether fiscal multipliers vary with business cycles is a question that has become particularly relevant to economists and policy makers since then, and this relevance will most likely remain, as governments struggle to reactivate economies and get through the current global economic conditions.

The so-called Fiscal Multiplier (FM) quantifies the effect that a shock in a fiscal policy instrument exerts on some economic outcome of interest, typically the gross domestic product. More precisely, Spilimbergo et al. (2009) define FMs as “the ratio of change in output to an exogenous change in a fiscal instrument with respect to their respective baselines”. FMs have been subject of a long history of theoretical debates among economists, where Keynesians propose fiscal policies as suitable instruments for stabilizing economic cycles, while Monetarists discard them to have any permanent effects on output (Mustea, 2015; Perotti, 2007; Woodford, 2011). The possible channels and mechanisms through which fiscal policies may transmit and affect other economic outcomes are manifold (Perotti, 2007; Hall, 2009; Woodford, 2011; Michaillat, 2014; Gechert, 2017), and may vary among economies or over time (Barrell et al., 2012, 2009). Unsurprisingly, estimates of FMs vary greatly across studies (Banerjee and Zampolli, 2019; Hall, 2009; Gechert and Rannenberg, 2018, see also the review provided in Section 2 of this work).

For the case of Chile, a single study addressing directly the cycle dependence of FMs has been put forth by Allegret and Lemus (2019), who find significant differences for the FM of government spending during recessions and expansions, with the estimated FM being larger during periods of economic downturn. A couple of studies examining FMs for Chile by means of a comparable methodology can be found. Differing mainly in the used data and the consideration of linear models that do not distinguish between different economic cycles, Cerda et al. (2005) conclude an overall null effect of fiscal policies in the long term, while Fornero et al. (2019) find small but significant positive multipliers for government consumption.

As it has become a regular practice in the empirical literature, Allegret and Lemus adopted a threshold vector autoregressive model (TVAR) to capture the nonlinearities emanating from the economic cycles. Their identification strategy consists of assuming a recursive model structure (i.e. a lower triangular covariance decomposition) based on assumptions of Blanchard and Perotti (2002), to finally estimate the FMs by means of linear impulse response functions (IRFs).

By implication, the authors assume that the state of the business cycle remains unaffected in the aftermath of the presumed fiscal shocks. Recently, it has been found for the U.S. that the outcome of this widespread empirical approach is not necessarily robust after lifting the lower triangular recursion and using impulse responses that account for the intrinsic nonlinearity of TVARs (Laumer and Philipps, 2020).

As an alternative to assuming a lower triangular structural pattern in an ad-hoc manner, more agnostic identification schemes have been proposed recently (Matteson and Tsay, 2017; Moneta et al., 2012) based on the uniqueness of independent components exhibiting non-Gaussian marginal distributions (for applications of this data-based approach to identification in structural VARs (SVARs) see, e.g., Gouriéroux et al., 2017; Herwartz, 2018; Moneta and Pallante, 2020; Guerini et al., 2020). Moreover, to quantify the FMs of interest the restrictions implied by linear IRFs can be relaxed by means of so-called generalized impulse response functions (GIRFs) introduced by Koop et al. (1996). As a particular merit, GIRFs can conceptually adapt to state dependencies as formalized in a TVAR framework. In this work, we investigate if the main findings of Allegret and Lemus (2019) for the Chilean economy remain robust after relaxing both the ad-hoc assumption of a recursive structural model and the use of linear IRFs in the context of the benchmark TVAR. In doing so we i) provide further insights into the FMs of a developing economy and updated estimates thereof, ii) introduce data-based identification by means of independent component analysis (ICA) into a TVAR setting, and (iii) trace the effects of independent component shocks within a framework of GIRFs which naturally adapt to regime dependence and, hence, to the intrinsic non-linearity of TVARs.

Conditioning on slightly different data, we can largely replicate core findings of Allegret and Lemus (2019). Specifically, using a recursive structural model and common linear IRFs yields evidence for sizeable and significant FMs which are stronger if triggered by expansionary spending shocks during periods of low economic growth in comparison with periods of higher growth rates. In addition, contractionary revenue shocks do not appear to have significant effects in neither situation. These core findings remain robust when adopting flexible nonlinear GIRFs in place of linear IRFs. When relaxing the assumption of a recursive model structure in the framework of a more agnostic ICA-based identification, however, core insights from the restrictive benchmark approach lack robustness. Aligning with similar results of Caggiano et al. (2015); Ramey and Zubairy (2018) and Laumer and Philipps (2020), we find no significant differences in neither government spending nor government revenue multipliers when comparing economic states of relatively lower and higher growth rates. Moreover, estimates using the agnostic approach show in general no significant FMs. In this respect, results from a recursive model structure align with findings of Allegret and Lemus (2019) and Fornero et al. (2019), while ICA identification yields results similar to findings of Cerda et al. (2005) for Chile and Holland et al. (2020) for Brazil as another Latin American economy.

Our findings suggests that results from previous studies could reflect the ad-hoc imposition of a hierarchical model structure (i.e. of a Cholesky factorization of the reduced form covariance). Such an imposition restricts the model to accommodate the interaction between the variables in rigid manner. Relaxing these rigidities by adopting a more agnostic identification scheme that build upon the uniqueness of independent non-Gaussian shocks results in finding no significantly different FMs for periods of (relatively) high versus low economic growth.

The remainder of this paper is structured as follows. Section 2 resumes the empirical FM literature. Section 3 provides a detailed description of our empirical approach, the model, the identification strategy and the data. Section 4 discusses our estimation results. Section 5 concludes. In addition, some methodological details are described inAppendix A. Variable definitions and data sources are provided in Appendix B. Some intermediate estimation results can be found in Appendix C (marginal effects, model eigenvalues, normality tests and covariance matrix estimates).

2. Fiscal Multiplier literature

2.1 General overview and main findings

The FM refers to the ratio of change in GDP to the change in the fiscal policy instrument that causes it. As an example, a government spending multiplier of 0.2 implies that a one billion US Dollar expansion of fiscal spending will rise GDP by 200 million US Dollar. On the one hand FMs allow for a classification with regard to the considered time span i.e., impact or cumulative FMs with the latter referring typically to horizons between two or three years. On the other hand one might categorize FMs according to the nature of the shocks, i.e., spending vs. revenue shocks. Dynamic stochastic general equilibrium (DSGE) and VAR models have been traditionally used for FM estimation (Ramey, 2016; Woodford, 2011; Mustea, 2015). The literature following the family of VAR models mostly builds upon the work of Blanchard and Perotti (2002). We next provide a brief chronological summary of the most relevant empirical literature, starting from works using linear VAR models in the early 2000's to results of more recent nonlinear modelling frameworks. [2]

Based on linear VARs, early FM studies find, in general, different effects for spending and revenue shocks. Taking some studies that use US data as an example, Blanchard and Perotti (2002) derive from quarterly data for the period 1947 to 1997 that spending FMs are higher at impact (about 0.8) than revenue multipliers (about 0.7), while the relation reverses after one year (0.5 for spending and 0.7 for revenue multipliers). Perotti (2005) analyses annual data from 1960 to 2001 and finds spending multipliers above unity after one year (1.4) reaching to 2.2 in a three years period, while tax multipliers evolve from 1.2 at the end of the first year to 0.2 by the third. Using quarterly data for the period 1955 to 2000 and identification by means of sign restrictions, Mountford and Uhlig (2009) detect spending multipliers going from 0.65 at quarter one to a negative value of -0.74 after two years, and revenue multipliers rising from 0.28 at the first quarter to 2.05 after eight quarters. Tenhofen and Wolff (2007) condition their analysis on quarterly data from 1947 to 2006 in an expectation extended VAR and find negative spending multipliers. Afonso and Sousa (2012) employ a Bayesian SVAR approach using quarterly data from 1971 to 2007 and find small positive effects of spending and revenue shocks on GDP. In parallel, DSGE-based studies from this period find in general spending multipliers to be larger than revenue multipliers, although the magnitudes of the estimations vary largely from estimated FMs close to zero to above one (see, for example, An and Schorfheide, 2007; Barrell et al., 2009, 2012).

The rise of consolidation fiscal policies after the government deficits led by the Great Recession, gave a strong impulse to an already growing FM literature, leading upfront the discussion whether FMs may be dependent on the economic state (Gechert and Rannenberg, 2018; Woodford, 2011; Mustea, 2015; Ramey, 2016). Gechert and Rannenberg (2018) performed a meta analysis using FM estimations from 98 studies published from 1992 to 2013 that allow for regime differentiation and employ single equation models. They conclude government expenditure multipliers to be larger during downturns, and tax multipliers to have no significant difference across business cycle regimes and to be overall smaller than expenditure multipliers. Representing DSGE-based modeling approaches, Barrell et al. (2009) and Barrell et al. (2012), also find spending multipliers to be larger during recessions.

[2] The vast quantity of studies available render a complete review beyond the scope of this paper. As the estimation methodologies evolve throughout our exposition, we will cite some remarkable examples illustrating the main results and the follow up discussion, along with some results from the DSGE-based literature.

The relation between FMs and the economic cycles became particularly relevant after the work of Auerbach and Gorodnichenko (2012). Using a smooth transition regime-switching SVAR model and quarterly US data for the period 1947 to 2008, these authors hint at the role of the (endogenous) economic cycle and “find large differences in the size of spending multipliers in recessions and expansions with fiscal policy being considerably more effective in recessions than in expansions”. Inquiring these results further, a sizeable TVAR FM literature emerged (e.g., Batini et al., 2012; Baum and Koester, 2011; Baum et al., 2012; Afonso et al., 2018; Farrazzy et al., 2015; Allegret and Lemus, 2019; Holland et al., 2020). Although having somewhat mixed and inconclusive results overall, findings in this literature confirm main insights of Auerbach and Gorodnichenko (2012) and show generally larger spending multipliers during recessions than during expansions, and overall smaller revenue multipliers. For the case of the US, Baum et al. (2012) analyze quarterly data from 1965 to 2011 and find spending multipliers of 1.3 and revenue multipliers of -0.1 for expansions, while in recessions spending FMs are of about 1.8 and revenue FMs are of about 0.1 after one year. Batini et al. (2012) use quarterly data for the period 1975 to 2010, and find spending FMs of 0.33 and revenue FMs of 0.15 in expansions after one year, while in downturns spending and revenue FMs are about 2.18 and 0.16, respectively. With a focus on transition economies, Mirdala and Kameník (2017) run TVAR models with quarterly data for the Czech Republic, the Slovak Republic and Hungary and the period 1995 to 2015. Employing GIRFs they find larger spending multipliers during recessions in the Czech Republic and Hungary, while opposite results obtain for the case of the Slovak Republic. Çebi and Özdemir (2016) run a TVAR model for Turkey with quarterly data covering the period from 1995 to 2015. Using a Cholesky decomposition as identification strategy and linear IRFs, they find that the effectiveness of fiscal policy is larger in times of low growth compared with times of relatively high growth.

For the purpose of identification, most of the quoted studies follow arguments of Blanchard and Perotti (2002), and rely on a lower triangular Cholesky decomposition with government spending ordered first in the vector of variables. The work of Laumer and Philipps (2020) is a noteworthy exception in this regard, since these authors complement the lower triangular recursion with a sign restriction approach as advocated by Mountford and Uhlig (2009). Another crucial aspect concerns the impulse/response functions used in the computation of the FMs. A good part of these studies, including the influential work of Auerbach and Gorodnichenko (2012), uses linear IRFs for each state of the economy, assuming implicitly that the imposed fiscal stimulus will not provoke a state change (e.g., a switch from a low growth regime to a high growth regime or vice versa). To solve this issue, some studies employ GIRFs as suggested by

Koop et al. (1996) (e.g., Batini et al., 2012; Baum et al., 2012; Farrazzy et al., 2015; Laumer and Philipps, 2020).

Although the vast majority of studies trying to distinguish FMs between recessions and expansions focus mainly on developed economies, there is some recent work investigating cases of developing economies. Zhang et al. (2018) estimate a TVAR model for China with quarterly data from 1992 to 2014. Using GIRFs to determine FMs from recursive model structures as well as by means of sign restrictions, they find that China's FM tends to be procyclical with larger multipliers characterizing expansion periods. López-Vera et al. (2018) estimate a smooth transition TVAR with recursive structure and standard IRFs for Colombia with quarterly data from 1995 to 2015 and find that expenditure and revenue multipliers are larger during periods featuring negative output gaps. Holland et al. (2020) use quarterly data from 1997 to 2018 to estimate FMs for Brazil by means of a TVAR model as well as other estimation approaches. The TVAR estimations using recursive structural models and regular IRFs hint at larger multipliers for the expansion regime. However, these authors conclude that, overall, fiscal policy hardly exhibits any effect on output in Brazil.

2.2 Fiscal Multipliers in Chile

Turning to the specific case of FMs in Chile, earlier work has mostly dealt with linear SVARs. Cerda et al. (2005) find small negative spending and tax multipliers, and conclude that, overall, fiscal policy does not affect output. Restrepo and Rincón (2006) find a long-run spending multiplier in excess of unity, while a rise in taxes exerts a small negative effect on output. Suggesting the effectiveness of fiscal policies, Céspedes et al. (2011) use a DSGE model to estimate impact spending multipliers of 0.7 and a cumulative multiplier of 2.8 after two years. Fornero et al. (2019) find spending multipliers of 0.2 on impact and 0.6 in the long term. The only work so far for Chile that distinguishes between economic states is Allegret and Lemus (2019). Imposing recursive model structures within their TVAR model and using linear IRFs, these authors find a positive spending multiplier for recessions (0.35 on impact and 1.23 after 10 quarters, both significant), and a negative one for expansions (0.22 on impact and -0.56 after 10 quarters, both significant). Corresponding results for tax policies amount to small positive revenue multipliers for recessions (insignificant on impact and 0.2 significant after 10 quarters) and to insignificantly small multipliers for expansion regimes.

3. Methodology

Our empirical analysis starts with a replication of the study of Allegret and Lemus (2019). From this exercise we expect largely similar results as provided in the benchmark study, since our data are similar to those of Allegret and Lemus (2019) but not exactly the same.[3] Accordingly, we estimate a structural TVAR model, identify the structural shocks by means of lower triangular covariance decompositions to obtain linear IRFs and, finally, determine the model implied FMs. In a similar fashion as Laumer and Philipps (2020), we continue the analysis by relaxing some restrictive assumptions of the benchmark approach one-by-one. In a first step, we allow for eventual state changes to occur in response to a shock of interest and employ non-linear GIRFs instead of linear IRFs. Secondly, we relax the assumption of a recursive structural pattern (i.e. the lower triangular covariance decomposition), and opt for an agnostic identification method based on ICA. We next provide a more detailed description of the model, the identification strategy, the GIRFs, the determination of FMs and the model specification.

3.1 The structural TVAR model

TVARs have become a popular approach to capture non-linearities in economic time-series data (see, e.g., Hubrich and Teräsvirta, 2013, for a review of threshold models). Yet, applications of these models comprise a wide range of fields, e.g., monetary policy analysis (Allen and Robinson, 2015; Tena and Tremayne, 2009; Calza and Sousa, 2006; Schmidt, 2020), financial market models (Balke, 2000), real exchange-rate and price differential models (Lo and Zivot, 2001). TVARs have been generally promoted for modeling and analyzing business cycles fluctuations (Koop et al., 1996; Galvão, 2003; Grynkiv and Stentoft, 2018), and they are particularly popular in the FM literature, where a growing body of work emerged after the Great Recession (e.g., Batini et al., 2012; Baum and Koester, 2011; Baum et al., 2012; Mirdala and Kameník, 2017; Allegret and Lemus, 2019).

TVARs are piecewise linear models which chain the dynamics of a set of variables over two or more distinct states or regimes, defined by an observed (endogenous or exogenous) transition

[3] We follow closely the data construction procedure of Allegret and Lemus (2019). However, as we did not have access to the full original data set used by these authors, some slight differences are to be expected, for instance, due to updates of data-sources. Moreover, we have used the X13-ARIMA seasonal adjustment method instead of the X11 employed by Allegret and Lemus (2019), and added two more years of observations to the data.

variable joint with threshold values (Hansen, 1996, 1997; Tsay, 1998; Galvão, 2003). In a structural form and with given presample values, a K-dimensional TVAR process z_t reads as

$$z_t = c^{(s)} + \sum_{p=1}^{P} A_p^{(s)} z_{t-p} + B^{(s)} \varepsilon_t, \quad t = 1, ..., T. \tag{1}$$

where $c^{(s)}$ is a deterministic (intercept) term and P is the (common) lag order. The index s, $s = 1, ..., S$, in (1) indicates that the model specification is state specific. By assumption, the orthogonalized structural shocks in ε_t are serially uncorrelated, have mean zero and - without loss of generality - unit variances, i.e. $Cov[\varepsilon_t] = I_K$, where I_K is the K-dimensional identity matrix. Reduced form residuals $u_t^{(s)} = B^{(s)}\varepsilon_t$ are of mean zero and subject to contemporaneous correlation according to state specific positive definite covariance matrices $Cov[u_t^{(s)}] = \Sigma^{(s)}$. Let γ_{t-d} be the transition variable and γ_{t-d} its value at time $t - d$, where d is a fixed positive integer value. The state s at time t is determined as

$$s_t\left(\gamma_{t-d}\right) = \{1 \quad if\, \gamma_{t-d} \le m_1;\ 2 \quad if\, m_1 < \gamma_{t-d} \le m_2;\ \vdots\ S-1 \quad if\, m_{S-2} < \gamma_{t-d} \le m_{S-} \tag{2}$$

where m_j, $j = 1, ..., S - 1$, are fixed threshold values, and the delay d denotes the number of time periods it takes for the model to change from one regime to another once a threshold is crossed. With known values for P, S, d and $m_j, j = 1.2,.., S - 1$, the model in (1) can be estimated by OLS by subdividing the sample according to the distinct regimes. Tsay (1998) suggests a methodology for joint estimation of the delay d, the thresholds m_j's and the state specific parameters $c^{(s)}$, $A_p^{(s)}, p = 1, ..., P$ and $\Sigma^{(s)}$.[4] As an alternative, however, the delay d - as well as the transition variable γ_t and the number of regimes S - are often selected a-priory, due to the large number of parameters subject to estimation (see, e.g, Baum and Koester, 2011, Batini et al., 2012, Baum et al., 2012).

[4] The joint estimation procedure relies on model selection, by trying all possible threshold values present in the data - provided a sufficiently large fraction of the available sample is left in each regime for estimation - and a finite set of possible values for d. The values for d and m_j, $j=1,...,S-1$, that minimize a likelihood based selection criterion - usually AIC - are kept. With given common lag order P the selection can also be made by selecting the model that obtains the minimum sum of squared residuals (Tsay, 1998, Lo and Zivot, 2001).

3.2 Shock identification strategy

Similar to the case of standard VAR models as motivated by Sims (1980), the structural shocks ε_t are unidentified in TVAR models, hidden within the infinitely many possible decompositions of the reduced form covariance matrices $\Sigma^{(s)}$. Retrieving the structural shocks has generally relied on theoretical assumptions, and the search for some sort of contemporaneous or long–run structural relations (see, e.g., Mustea, 2015; Laumer and Philipps, 2020, for examples in the FM literature). As mentioned above, in the FM literature authors have generally followed structural approaches based on the work of Blanchard and Perotti (2002). Their main identifying assumption is that a government cannot react and adapt its expenditures to changes in output within one quarter (the usual data frequency). This implies imposing a structural zero effect of shocks to output on government spending. Although Blanchard and Perotti (2002) go further by imposing some non-zero restrictions to the covariance matrix using elasticity values from several sources, most studies following Blanchard and Perotti (2002) employ a lower triangular Cholesky decomposition, with the variable ordering being government consumption, output, government revenues (and eventually further variables). This approach was also adopted by Allegret and Lemus (2019).

Drawing upon Allegret and Lemus (2019), we start our empirical exercise assuming a lower triangular covariance factor, and then relax this restrictive assumption in favor of a more agnostic and data-driven structural model. As an alternative identification scheme we adopt ICA-based identification as described in Matteson and Tsay (2017). Similar shock identification strategies have been recently implemented in SVARs (e.g., Gouriéroux et al., 2017; Herwartz, 2018; Moneta and Pallante, 2020; Guerini et al., 2020). In comparison with the standard lower triangular recursion, ICA has the advantage to be completely agnostic with regard to possible parameter restrictions, and relies only on data characteristics. In particular, it has been shown that the ICA approach results in a unique structural parameter matrix if the underlying structural shocks are independent (not just orthogonal) and at most one of these shocks exhibits a marginal Gaussian distribution (Comon, 1994).[5] Let Us represent the matrix of all reduced form residuals consistent with regime s in the data, so that

[5] The independence assumption goes beyond the standard orthogonality condition for the structural shocks. Although this might seem restrictive, the objective of IRFs and GIRFs is to study the effects of shocks that occur in isolation or independently of each other. In addition, the requirement of non Gaussianity is a data characteristic that can be subjected to testing.

$$U_s = B^{(s)}E_s^{'}, \quad (3)$$

where E_s is a matrix containing K columns of structural shocks for regime s, and $B^{(s)}$ is the nonsingular $K \times K$ dimensional mixing matrix. Under mutual independence of the columns of E_s and allowing for at most one series of shocks exhibiting a Gaussian distribution, Matteson and Tsay (2017) suggest to minimize the joint distance covariance between the columns of E_s to find $B^{(s)}$.[6] Matteson and Tsay (2017) also show that the suggested procedure is consistent, and argue that it works well in simulations and real data examples.

3.3 Generalized impulse response functions

Although the TVAR model described in (1) is linear within a regime, the overall model specification is non-linear. Accordingly, the typical IRFs derived from VAR models might suffer from misspecification. As an alternative to linear IRFs, GIRFs as suggested by Koop et al. (1996) can be straightforwardly constructed to cope with the intrinsic non-linearity. Let Ω_{t-1} summarize the state of the dynamic system in time $t-1$. Conditional on Ω_{t-1}, a GIRF at forecast horizon h obtains as the difference between two expectations, i.e.

$$GIRF_t\left(h, \delta_t, \Omega_{t-1}\right) = E\left(\delta_t, V_{t+h}, \Omega_{t-1}\right) - E\left(V_{t+h}, \Omega_{t-1}\right). \quad (4)$$

In (4), $E\left(\delta_t, V_{t+h}, \Omega_{t-1}\right)$ signifies the expectation of z_{t+h} conditional on the information set Ω_{t-1} (which includes information about the initial state s) and the presumption that an exogenous shock δ_t hits the system in time t. The shock vector δ_t will have magnitude δ in a particular position of interest and zero otherwise, and occurs in addition to the system's 'natural noise' $V_{t+h} = (\varepsilon_t, \varepsilon_{t+1}, ..., \varepsilon_{t+h})$, whose elements exhibit the unconditional distribution of the TVAR innovations. For tracing out the effects of the shock δ_t, $E\left(V_{t+h}, \Omega_{t-1}\right)$ is the corresponding expectation derived under the assumption that the system is not hit by an exogenous shock, or, put differently, that the system is affected just by the disturbances in V_{t+h}. To obtain

[6] The distance covariance is a measure of dependence between two (groups of) random vectors. Its population counterpart is the distance between the joint characteristic function of these random variables and the product of the marginal characteristic functions (Székely et al., 2007; Székely and Rizzo, 2009). The detection of $\mathrm{B}(s)$ requires the solution of a non-linear optimization problem. For computation purposes we use the R package steadyICA of Risk and Matteson (2015).

unconditional GIRFs, the moment evaluation in (4) is repeated for each history Ω_{t-1} and averaged subsequently conditional on the initial regime s. GIRFs for each regime s obtain as

$$GIRF^{(s)}\left(h, \delta_t\right) = \frac{1}{|S|}\sum_{t\in S} GIRF_t\left(h, \delta_t, \Omega_{t-1}\right) \tag{5}$$

where $GIRF_t$ is defined in (4) and $|S|$ is the number of histories starting in state s.

Apparently, the main difference between GIRFs and IRFs is that the latter are conditional on setting all disturbances in V_{t+h} - the disturbances other than the exogenous shock - to values of zero, while GIRFs are unconditional in this sense. Moreover, GIRFs allow the expectations in the right side of (4) to vary across regimes independently at any time point if the considered dynamic profiles invoke some threshold crossing in the TVAR system. to values of zero, while GIRFs are unconditional in this sense. To implement this perspective, the estimation of GIRFs builds upon replications of bootstrap samples $\widetilde{V}_{t+h} = (\widetilde{\varepsilon}_t, \widetilde{\varepsilon}_{t+1}, ..., \widetilde{\varepsilon}_{t+h})$, where vectors $\hat{\varepsilon}_i$, $t\leq i\leq t + h$ are drawn with replacement from $\left\{\hat{\varepsilon}_t\right\}_{t=1}^{T}$. For a detailed description of the algorithm used for the computation of the GIRFs we refer the reader to Appendix A. It is noteworthy that the random variables in $\widetilde{V}_{t+h}$ are drawn from orthogonalized estimates of residuals $\left\{\hat{\varepsilon}_t\right\}_{t=1}^{T}$. Hence, the adopted identification strategy is a key determinant of this process outcome, samples $\left\{\hat{\varepsilon}_t\right\}_{t=1}^{T}$ differ when using either an a-priori suggestion of a lower triangular recursion or of independent components.

3.4 The Fiscal Multiplier

Two measures of FMs can be found in the literature, the impact multiplier, which is determined at the time when the shock hits the system, and the cumulative multiplier, which adds longer term effects up to a given horizon. Let y_t denote output, g_t government spending and τ_t government revenues in per capita terms. FMs for both government spending (SM) and government revenues (RM) up to horizon H can be derived, respectively, as

$$SM(H) \approx \frac{\sum_{h=0}^{H} dlog\left(y_{t+h}\right)}{\sum_{h=0}^{H} dlog\left(g_{t+h}\right)} * \frac{\bar{y}}{\bar{g}} \text{ and } RM(H) \approx \frac{\sum_{h=0}^{H} dlog\left(y_{t+h}\right)}{\sum_{h=0}^{H} dlog\left(\tau_{t+h}\right)} * \frac{\bar{y}}{\bar{\tau}} \quad (6)$$

where $dlog\left(y_{t+h}\right)$, $dlog\left(g_{t+h}\right)$ and $dlog\left(\tau_{t+h}\right)$ comes from the IRFs and GIRFs estimates using a shock to expenditures and revenues to determine $SM(H)$ and $RM(H)$, respectively. Moreover, $\bar{y}$, $\bar{g}$ and $\bar{\tau}$ typically refer to sample means of per capita output, per capita government spending and per capita government revenues, respectively (Céspedes et al., 2011, Allegret and Lemus, 2019).[7] Impact multipliers obtain from setting the horizon $H = 0$ in (5), while choices of $H = 4,\ 8, 10$ are typical for the determination of cumulative multipliers.

3.5 The empirical model and the data

Following Allegret and Lemus (2019), we run two TVAR specifications. The first setup (model 1) is based on the Blanchard and Perotti (2002) model. Due to its parsimony this specification has been widely employed as benchmark for fiscal multiplier TVAR models (see, for example, Batini et al., 2012; Baum et al., 2012; Holland et al., 2020; Soederhuizen et al., 2019; Allegret and Lemus, 2019; Mirdala and Kameník, 2017; Çebi and Özdemir, 2016). In model 1, the vector of endogenous variables contains the stationary quarter-on-quarter growth rates of real government expenditures (i.e. first differences of quarterly aggregates in natural logarithm), ($z_{1t} = \Delta \log log \left(g_t\right)$), real output ($z_{2t} = \Delta \log log \left(y_t\right)$) and real net taxes ($z_{3t} = \Delta \log log \left(\tau_t\right)$) in per capita terms. For the second specification (model 2) real interest rates in differences are added to the system ($z_{4t} = \Delta r_t$). As in Allegret and Lemus (2019), the vectors of endogenous variables for models 1 and 2 are $z_t = (\Delta \log log \left(g_t\right), \Delta \log log \left(y_t\right), \Delta \log log \left(\tau_t\right))$ and $z_t = (\Delta \log log \left(g_t\right), \Delta \log log \left(y_t\right), \Delta \log log \left(\tau_t\right), \Delta r_t)$, respectively.

Regarding the selection of variables and the employed model specification two remarks are worth making: First, as the relative price of inter-temporal consumption, variations in the interest rate have a direct effect on private consumption decisions. Moreover, interest rate changes reflect the interaction between fiscal and monetary policies, and play an important role for the effects of fiscal policies on output (Spilimbergo et al., 2009; Batini et al., 2012; Fornero et al.,

[7] Although the possible bias for including ratios of sample means of trending variables in the computation of FMs has been pointed out in the literature (Owyang et al., 2013, Ramey, 2016), it remains the standard way to approximate FMs from IRFs/GIRFs of variables in logarithms.

2019, and others). Monetary policies adjusting to government expansions should imply changes in the real interest rate that crowd out private consumption and attenuate the effect of the fiscal stimulation, while sticky interest rates would lead to multipliers closer to unity. Multipliers in excess of unity could be achieved in the case of a reaction of the interest rate that pushes consumption in the same direction of a fiscal stimulus (Woodford, 2011). Second, despite its widespread use for analysing fiscal policies in small open economies (SOEs) (see, for example, Restrepo and Rincón, 2006; Allegret and Lemus, 2019; Holland et al., 2020), the considered model appears more suited for analysing closed economies. Unlike some authors who opt for modeling SOEs by including related control variables, as, for instance, terms of trade data or measures of openness (see, for example, Sanches and Galindo, 2013; López-Vera, et al., 2018), we follow closely the benchmark study of Allegret and Lemus (2019) for two reasons. On the one hand, a main objective of our study is to compare results obtained from distinct identification methods. On the other hand, as the number of parameters to be estimated is an important concern in a TVAR setting with short to medium time series dimension, we opt for a more parsimonious lower-dimensional model specification.

We use quarterly data for the Chilean economy, covering the period from 1990:q1 to 2019:q4.[8] Data sources and definitions for the variables under scrutiny are provided in Appendix B. Table 1 displays some descriptive statistics and unit root diagnostics for the variables employed. Both unit root tests performed, Augmented Dickey-Fuller (ADF) and Phillips-Perron, obtain a rejection of the null hypothesis of a unit root for all variables in differences. Plots of the series used in the main model can be found in Figure 1 for visual inspection.

Table 1. Descriptive statistics of the variables and unit root tests

					ADF		Phillips-Perron	
		variable	mean	variance	statistic	*p*-val	statistic	*p*-val
Levels	GDP*	$\log log\left(y_t\right)$	7.349	0.136	-1.880	0.342	-1.509	0.529
	Gov. Spending*	$\log log\left(g_t\right)$	5.764	0.173	-0.490	0.894	-0.405	0.909
	Gov. Revenues*	$\log log\left(\tau_t\right)$	5.779	0.158	-1.837	0.362	-1.816	0.373

[8] We left out the COVID pandemic as the expansionary fiscal policy in Chile during this period was largely driven by vaccine purchases and direct transfers to population, which might imply an overly specific policy response in the context of a more general fiscal policy analysis. Our main results remain robust to using the sample period 1990:Q1 to 2017:Q4, as in Allegret and Lemus (2019).

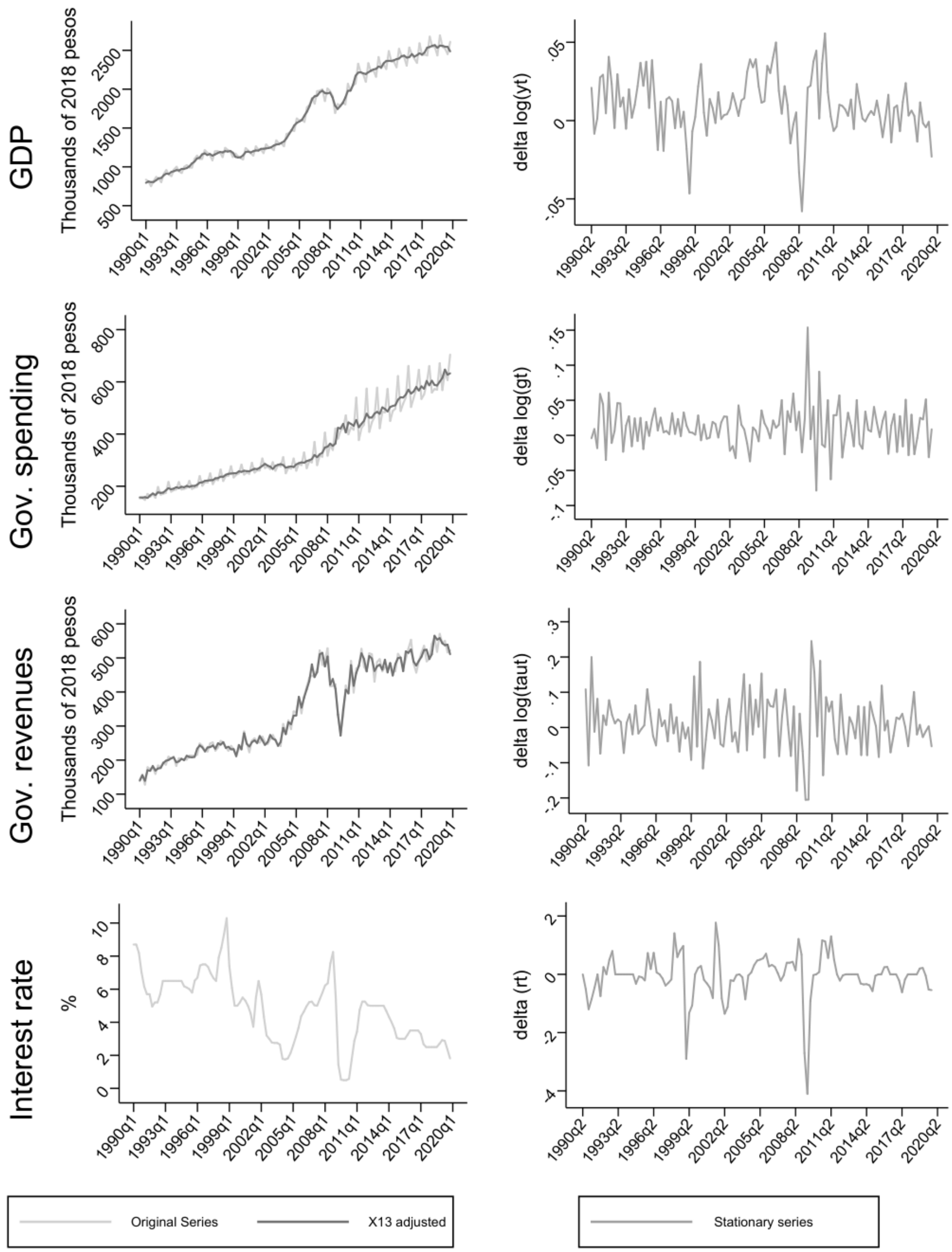
	Interest Rate	r_t	4.781	4.136	-2.255	0.187	-2.742	0.067
Differences	GDP**	$\Delta \log log (y_t$	0.959	3.358	-6.611	0.000	-6.714	0.000
	Gov. Spending**	$\Delta \log log (g_t$	1.169	8.963	-15.592	0.000	-16.494	0.000
	Gov. Revenues**	$\Delta \log log (\tau_t$	1.091	62.413	-14.500	0.000	-14.669	0.000
	Interest Rate	Δr_t	-0.058	0.565	-6.573	0.000	-6.344	0.000

* Original y_t, g_t and τ_t series in thousands of pesos of 2018, displayed results are for the log transformed data.

** Multiplied by 100.

Critical values for both unit root tests, Augmented Dickey-Fuller (ADF) and Phillips-Perron, are -3.504, -2.889 and -2.579 at the 1%, 5% and 10% significance level, respectively.

Figure 1. Plots for the time series variables. Left hand side column: Original series; right: Series in (log) differences as used in the TVAR model.



GDP
Thousands of 2018 pesos
delta log(yt)
Gov. spending
Thousands of 2018 pesos
delta log(gt)
Gov. revenues
Thousands of 2018 pesos
delta log(taut)
Interest rate
%
delta (rt)
Original Series
X13 adjusted
Stationary series

The considered TVARs build upon two regimes $s = 1, 2$, depending on the per capita GDP growth (the transition variable γ_t) being below or above some threshold value m, which we estimate jointly with the dynamic model parameters and the intercept terms. Following the reference study of Allegret and Lemus (2019), the delay parameter is not subject to estimation and set to $d = 1$. We indicate a period following a growth rate below the threshold value with $s = 1$ (i.e. a low-growth regime). In analogy, $s = 2$ indicates an expansionary or high-growth state, where the growth rate has been above the threshold value in the previous period. Also following the benchmark study, we estimate fiscal multipliers for government spending and revenues assuming positive shocks of size one standard deviation. Hence our spending multiplier refers to expansionary policies (i.e. a one standard deviation increase in government spending), while the revenue multiplier refers to contractionary policies (i.e. a one standard deviation increase in tax revenues). Formally, the shock vectors used in our GIRF computations have the form $\delta_t^{SM} = (1, 0, 0)$, $\delta_t^{RM} = (0, 0, 1)$ for model 1 and $\delta_t^{SM} = (1, 0, 0, 0)$, $\delta_t^{RM} = (0, 0, 1, 0)$ for model 2.

For inferential purposes we employ a so-called recursive design wild bootstrap as suggested by Goncalves and Kilian (2004). Bootstrap replications of the data read as

$$z_t^* = \hat{c}^{(s)} + \sum_{p=1}^{P} \hat{A}_p^{(s)} z_{t-p}^* + u_t^*, \quad t = 1, 2, ..., T, \tag{7}$$

where $\hat{A}_p^{(s)}$, $p = 1,.., P$, and $\hat{c}^{(s)}$, $s = 1, 2$, are estimated TVAR parameters. The bootstrap reduced form residuals are $u_t^* = \omega_t \hat{u}_t^{(s)}$, where the scalar ω_t is drawn independently of the data and exhibits a Rademacher distribution (i.e., $p(\omega_t = 1) = p(\omega_t = -1) = 0.5$). In (7) the process is conditional on the threshold value estimated by means of the original data, which is used to define the regime s at each period t depending on z_{t-1}^*. After generation of the bootstrap data they are subjected to the same estimation steps as the original data.

4. Results

4.1 TVAR estimation

As it is common in the literature (see, for example, Farrazzy et al., 2015; Baum and Koester, 2011), lag order selection is based on pooled samples, i.e. on a standard linear VAR, and the obtained lag order is subsequently imposed on the TVAR specification. For both specifications, model 1 and model 2, the Hannan-Quinn and Schwartz criterionobtain their minimum when choosing $P = 1$.[9]

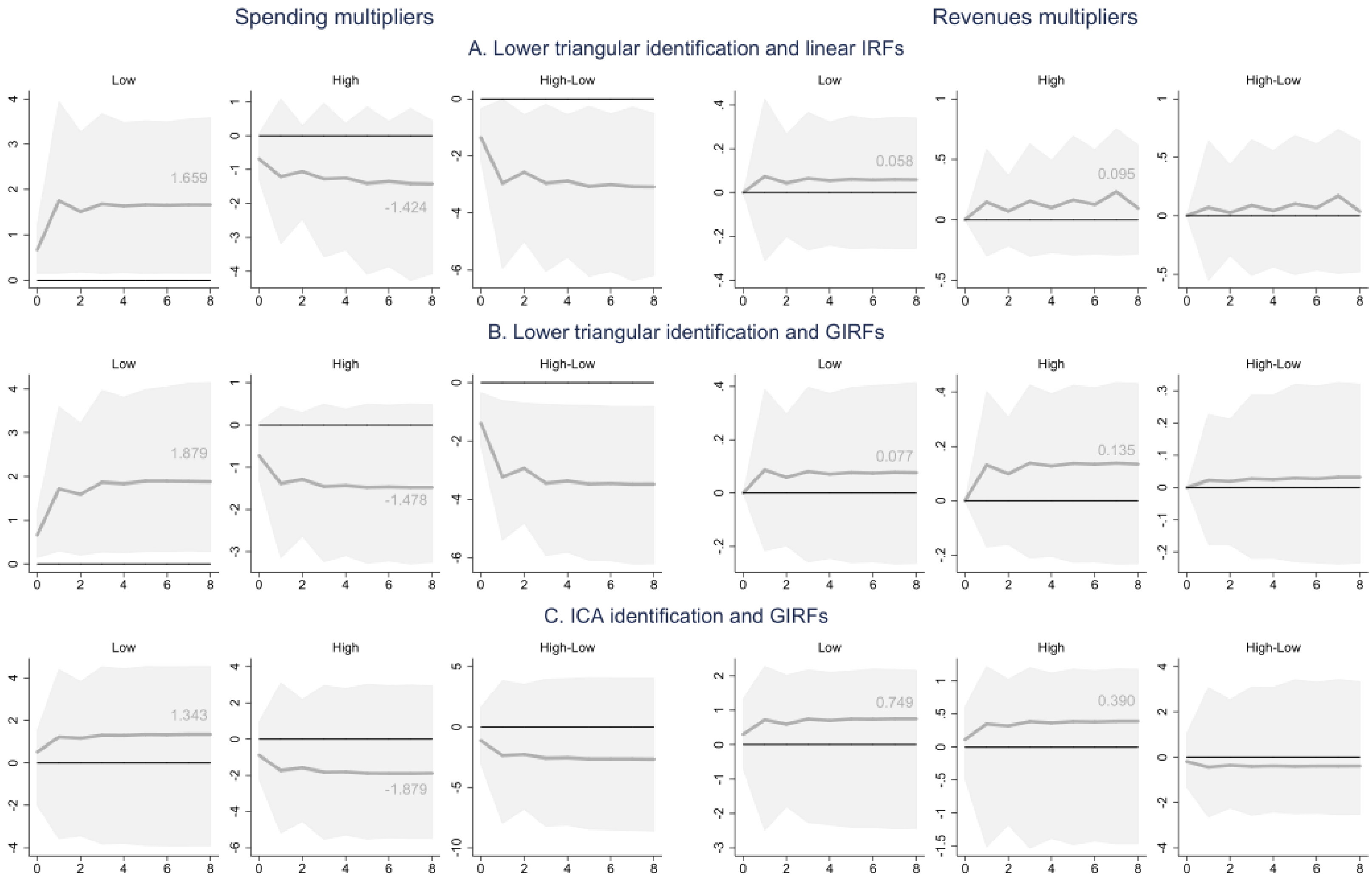
Following the procedure suggested by Tsay (1998) obtains threshold values of 0.018 (i.e., a 1.8% growth rate) for model 1 and of 0.017 (1.7% growth rate) for model 2, which slightly exceed their counterparts in the benchmark study of Allegret and Lemus (2019) (i.e., 1.1% for model 1 and 1.0% for model 2).[10] Accordingly, the low and high-growth regime cover 85 (72.03%) and 33 (27.97%) observations, respectively, in the case of model 1. For model 2 we have that 82 (69.49%) and 36 (30.51%) observations are attributed to the low and high-growth regime, respectively. Similar to findings of Farrazzy et al. (2015) for the USA, the Chilean economy spend most of its time in a tight economic regime. Parameter estimates for both models, as well as the estimated reduced form covariance matrices and other intermediate estimation results can be found in Appendix C.

4.2 Recursive model structures

In their panels A Figure 2 and Figure 3 show cumulative fiscal multipliers for models 1 and 2, respectively, that are obtained from linear IRFs and a recursive model structure as suggested in Allegret and Lemus (2019). Similar to benchmark results of Allegret and Lemus (2019), we find significant spending multipliers for the low-growth regime that exceed unity, and insignificantly negative average spending multipliers for the high-growth regime. In the literature, average revenue multipliers are often found smaller than spending multipliers for shocks of a given size. We confirm this result for model 1. With a lack of significance, however, the average revenue multiplier changes from being positive in model 1 to negative in model 2. The differences of multiplier estimates between regimes are also indicated in the Figures. As it turns out, the replication of the benchmark model reveals significant state dependence of multipliers at all horizons for model 1. In the case of model 2, the difference between state specific cumulative multipliers become insignificant after two quarters.

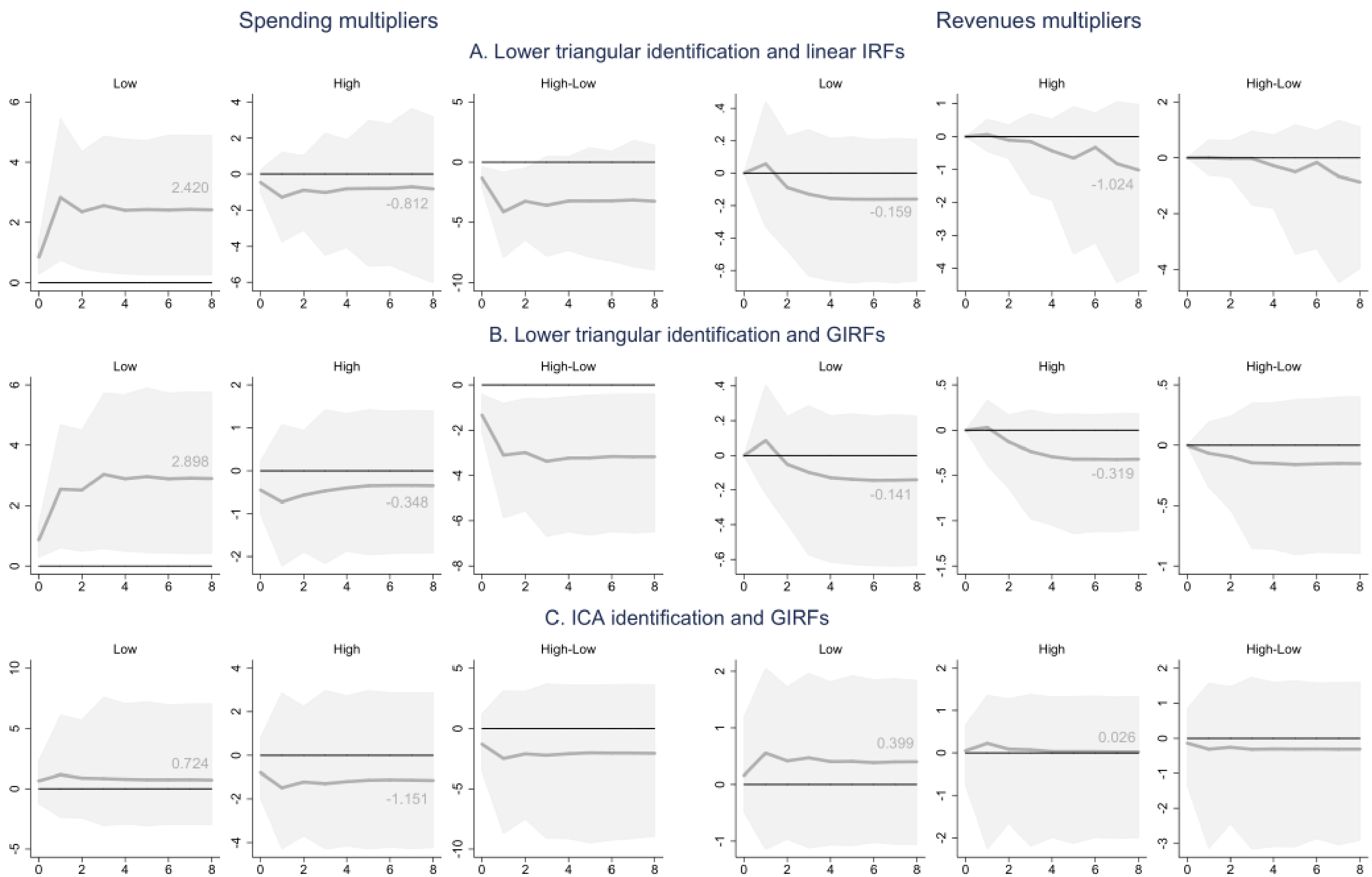
[9] We consider Akaike (AIC), Schwartz (BIC) and Hannan-Quinn (HQC) information criteria. As it turns out, a lag order of P = 1 minimizes two out of the three criteria. Moreover, opting for a more restrictive model order better aligns with the postulate of model parsimony in the present non-linear model context.
[10] All main results documented in this work are robust to using the threshold values of Allegret and Lemus (2019).

Figure 2. Cumulative FMs for Model 1



X axis in quarters. 90% bootstrap confident area. Numerical results are for horizon quarter 8.

Figure 3. Cumulative FMs for Model 2



For notes see Figure 2.

As in Laumer and Philipps (2020), we next relax the linearity assumption that is typical for conventional IRFs, and discuss FMs as implied by GIRFs that take account of potential regime changes in the aftermath of the shocks under scrutiny. Cumulative multipliers obtained from GIRFs are shown in the panels B of Figure 2 (model 1) and Figure 3 (model 2). Generally, results from using IRFs remain robust when using GIRFs to quantify FMs. A slight increase of average spending multipliers can be observed for both regimes in model 1. Conditional on model 2, the GIRF implied spending multipliers exceed the IRF results for the low growth regime, while they get closer to zero

in periods of higher growth. The significant difference between spending multipliers assigned to distinct regimes observed in model 2 is persistent and holds at all considered horizons. Overall, revenue multipliers still accord in general with the literature in being smaller than spending multipliers. Moreover, revenue multiplier estimates lack significance at conventional levels. Confirming results for linear IRFs, average revenue multipliers change from being negative in model 1 to positive in model 2. Somewhat differing from results for linear IRFs, however, GIRF implied revenue multipliers are of a similar pattern for both regimes and stay below unity.

4.3 Identification by means of independent components

We next relax the lower triangular identification assumption by using the more agnostic ICA approach. Results for identification by means of ICA are shown in panels C of Figure 2 (model 1) and Figure 3 (model 2). Dramatic changes can be seen, particularly for the spending multipliers that are implied by both models. Conditional on low-growth regimes, the 10% significance now vanishes for the revenue multipliers. Conditional on model 2, the average spending multiplier during recessions falls below unity. Moreover, the response differences across regimes lack significance throughout in both models.

Table 2 shows independence diagnostics for orthogonalized residuals of models 1 and 2. The population counterpart of the documented distance covariances is zero, if and only if the random variables subjected to testing are independent (Székely and Rizzo, 2009). As a first tool for independence diagnosis, we consider orthogonalized residuals as dependent, if the 5% and 95% quantiles of bootstrap distance covariance statistics do not cover a value of zero. With this criterion we find that subjecting model 2 to a recursive structure results in dependent structural shocks for the low growth regime in model 2. Moreover, conditional on the recursive model, the null hypothesis of having independent orthogonalized residuals is rejected with considerably larger frequencies throughout. Hence, unlike the shocks implied by the more agnostic identification scheme, shocks retrieved from a recursive model structure lack independence. While being orthogonal, these shocks can hardly be considered as fully exogenous, i.e. in a higher order sense they are subject to joint determination.

Table 2. Multivariate distance covariance statistics (multiplied by 100) and percentage of rejected tests for the null hypothesis of independent shocks.

ID-Scheme	Regime	Model 1				Model 2			
		Q5	Mean	Q95	H_0	Q5	Mean	Q95	H_0
Cholesky	Low	-0.37	2.21	5.23	46.40%	0.71	4.82	9.46	78.60%
	High	-5.15	0.66	6.75	11.20%	-6.48	0.1	7.34	13.40%
ICA	Low	-1.97	-0.3	1.73	3.20%	-2.54	-0.25	2.92	6.00%
	High	-8.16	-3.38	1.71	0.20%	-10.24	-5.21	0.52	0.20%

Q5, Q95 and 'mean' refer, respectively, to the 5th and 95th quantile and the empirical average of distance covariance statistics from 500 wild-bootstrap replications. H_0 indicates in percentages the frequency of rejections of the null hypothesis of independence with 10%significance out of 500 wild bootstrap replications.

Table 3 shows the estimated Cholesky factors and ˆB matrices for models 1 and 2. For the three baseline variables g, y and τ , the lower triangular sign pattern of the Cholesky matrices also holds for the ICA-identified structural parameter matrix, although all estimates loose significance. An increase in government spending contemporaneously raises the GDP in a low growth regime, although not in the high growth regime. GDP shocks seem to have a positive effect on government revenues and a negligible one on government spending, which is largely in line with the assumption of Blanchard and Perotti (2002), that output lacks a contemporaneous effect on government spending. When using ICA identification for both models, an increase in taxes invokes a contemporaneous yet insignificant increase in output for both regimes, an increase in spending for low-growth regimes and a decrease in spending for high growth regime. When inspecting the covariance matrices identified using a Cholesky decomposition for model 2, we observe a contemporaneous negative reaction of the interest rate to spending and a positive reaction to revenue shocks (this last one significant during high-growth regimes).

By implication, these estimates signify a crowding out effect of government expansions on private consumption. As another feature of the ICA-identified matrix for model 2, we observe a positive average response of interest rates to government spending shocks, clouding the previous hints of crowded out consumption for spending shocks. Also, the positive contemporaneous increase of interest rate following revenue shocks during high-growth regimes found using the imposed lower triangular structure looses its significance when using ICA identification.

Table 3. Estimated structural parameters (i.e. covariance factors, multiplied by 100) for models 1 and 2

Matrix	Regime	Equation	Model 1 g	Model 1 y	Model 1 τ	Model 2 g	Model 2 y	Model 2 τ	Model 2 r
Cholesky	Low	$\Delta \log log\left(g_t\right)$	2.636*	0.000	0.000	2.538*	0.000	0.000	0.000
		$\Delta \log log\left(y_t\right)$	0.375*	1.575*	0.000	0.457*	1.548*	0.000	0.000
		$\Delta \log log\left(\tau_t\right)$	-1.889	1.765*	5.554*	-1.923*	1.753*	5.529*	0.000
		Δr_t				-13.600	-14.236	10.421	53.442*
	High	$\Delta \log log\left(g_t\right)$	2.726*	0.000	0.000	2.818*	0.000	0.000	0.000
		$\Delta \log log\left(y_t\right)$	-0.403	1.559*	0.000	-0.267	1.436*	0.000	0.000
		$\Delta \log log\left(\tau_t\right)$	-1.086	0.963	7.241*	-1.130	0.283	7.152*	0.000
		Δr_t				-2.834	-0.151	26.312*	52.355*
ICA	Low	$\Delta \log log\left(g_t\right)$	2.335*	0.090	0.138	1.809*	0.072	0.309	-0.737
		$\Delta \log log\left(y_t\right)$	0.183	1.394*	0.293	0.208	1.324*	0.244	-0.437
		$\Delta \log log\left(\tau_t\right)$	-2.230	0.788	4.827*	-1.515	0.983	4.784*	1.000
		Δr_t				3.589	-3.669	2.195	51.641*
	High	$\Delta \log log\left(g_t\right)$	2.424*	0.140	-0.391	2.422*	0.323	-0.110	-0.114
		$\Delta \log log\left(y_t\right)$	-0.407	1.420*	0.165	-0.357	1.237*	0.039	0.016
		$\Delta \log log\left(\tau_t\right)$	-0.076	0.127	6.779*	-0.417	-0.214	5.663*	1.895
		Δr_t				1.353	-1.579	9.184	51.121*

* 0 not included in the Q5 - Q95 bootstrap quantiles interval. For more detailed information on bootstrap quantiles see Table 6 (model 1) and Table 7 (model 2) in Appendix C.

5. Conclusion

We study the dependence of fiscal multipliers in Chile on the economic cycle. For this purpose we relax some restrictive assumptions that have been made in a previous benchmark study of Allegret and Lemus (2019). In particular, we employ flexible generalized impulse responses (GIRFs) instead of stylized linear impulse response functions, and opt for a data-based identification of the structural parameter matrix instead of using an ad-hoc lower triangular recursion. Specifically, the identification scheme exploits the uniqueness of linear combinations of non-Gaussian independent components (Comon,1994). Thereby, this study is first in deriving non-Gaussian independent components within the non-linear setting of threshold VAR models.

In spite of slight differences with regard to the definition of variables our baseline results obtained from a most restrictive framework (i.e., linear IRFs and a recursive structural model) are in line with earlier findings of Allegret and Lemus (2019). Government spending multipliers are significantly state dependent on impact, above unity and significant conditional on the low growth regime and (insignificantly) negative for high growth regimes. The revenue multipliers appear to be overall smaller than the spending multipliers and lack significance.

With the imposition of less restrictive assumptions, i.e. identification by means of an agnostic data-based structural model, and the use of GIRFs that account for non-linear threshold dynamics our empirical FM results change in two important respects. First, we find no significant differences in neither spending nor revenue FMs. These results are in contrast to some earlier literature, but align with recent findings of Caggiano et al. (2015); Ramey and Zubairy (2018) and Laumer and Philipps (2020). Second, our estimates show in general no significant evidence for non-zero FMs. In this respect, results from the lower triangular identification scheme are supportive for findings of Allegret and Lemus (2019) and Fornero et al. (2019), while an agnostic identification scheme yields results that align with findings of Cerda et al. (2005) for Chile or Holland et al. (2020) for Brazil as another Latin American economy. Our findings suggests that results from previous studies could reflect the ad-hoc im-position of a hierarchical model structure (i.e. of a Cholesky factorization of the reduced form covariance). Relaxing these rigidities by adopting a more agnostic identification scheme that build upon the uniqueness of independent non-Gaussian shocks results in finding no significantly different FMs for periods of (relatively) high versus low economic growth.

References

Afonso, A., Baxa, J., and Slavík, M. (2018). Fiscal developments and financial stress: a threshold VAR analysis. *Empirical Economics*, 54(2):395–423

Afonso, A. and Sousa, R. M. (2012). The macroeconomic effects of fiscal policy. *Applied Economics*, 44(34):4439–4454.

Allegret, J.-P. and Lemus, A. (2019). Nonlinear effects of the Chilean fiscal policy. *Economía Chilena*, 22(3):132–153.

Allen, N. and Robinson, J. (2015). Monetary policy effects in a regime switching model. *Bank of Jamaica Working Paper*.

An, S. and Schorfheide, F. (2007). Bayesian analysis of DSGE models. *Econometric Reviews*, 26(2-4):113–172.

Auerbach, A. J. and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 42(2):1–27.

Balke, N. S. (2000). Credit regimes and nonlinear propagation of shocks. *The Review of Economics and Statistics*, 82(2):344–349.

Banerjee, R. and Zampolli, F. (2019). What drives the short-run costs of fiscal consolidation? Evidence from OECD countries. *Economic Modelling*, 82(2):420–436.

Barrell, R., Fic, T., and Liadze, L. (2009). Fiscal policy effectiveness in the bankingcrisis. *National Institute Economic Review*, 207:43–50.29

Barrell, R., Holland, D., and Hurst, I. (2012). Fiscal multipliers and prospects for consolidation. *OECD Journal: Economic Studies*, 2012(1):71–102.

Batini, N., Callegari, G., and Melina, G. (2012). Successful austerity in the United States, Europe and Japan. *IMF Working Paper 190*. International Monetary Fund.

Baum, A. and Koester, G. (2011). The impact of fiscal policy on economic activity over the business cycle - evidence from a threshold VAR analysis. *Deutsche Bundes bank Discussion Paper*, 03/2011.

Baum, A., Poplawski-Ribeiro, M., and Weber, A. (2012). Fiscal multipliers and the state of the economy. *IMF Working Paper* 286. International Monetary Fund.

Blanchard, O. and Perotti, R. (2002). An empirical characterization of the dynamic effects of changes in government spending and taxes output. *The Quarterly Journal of Economics*, 117(4):1329–1368.

Caggiano, G., Castelnuovo, E., Colombo, V., and Nodari, G. (2015). Estimating fiscal multipliers: News from a non-linear world. *The Economic Journal*, 125(584):746–776.

Calza, A. and Sousa, J. (2006). Output and inflation responses to credit shocks: Are there threshold effects in the Euro area? *Studies in Nonlinear Dynamics & Econometrics*,10(2):1253.

Çebi, C. and Özdemir, K. A. (2016). Cyclical variation of fiscal multiplier in Turkey. *Working Papers 1619*. Research and Monetary Policy Department, Central Bank of the Republic of Turkey.

Cerda, R. A., González, H., and Lagos, L. F. (2005). Efectos dinámicos de la política fiscal. *Cuadernos de Economía*, 42(125):63–77.

Céspedes, L. F., Fornero, J. A., and Galí, J. (2011). Aspectos no ricardianos de la política fiscal en Chile. *Economía Chilena*, 14(2):79–107.

Comon, P. (1994). Independent component analysis, a new concept? *Signal Processing*, 36(3):287–314.

Correa, V., Escandón, A., Luengo, R., and Venegas, J. (2002). Empalme PIB: series anuales y trimestrales 1986-1995, base 1996. Documento metodológico. *Working Papers 179*. Central Bank of Chile.

DIPRES (1990 to 2019). Estado de operaciones de gobierno (cuadro 2). *Dirección de Presupuestos, Gobierno de Chile*.

Farrazzy, S. M., Morley, J., and Panovska, I. (2015). State-dependent effects of fiscal policy. *Studies in Nonlinear Dynamics & Econometrics*, 19(3):285–315.

Fornero, J., Guerra-Salas, J., and Pérez, C. (2019). Multiplicadores fiscales en Chile. *Economía Chilena*, 22(1).

Galvão, B. A. (2003). Multivariate threshold models: TVARs and TVECMs. *Brazilian Review of Econometrics,* 23(1):143–171.

Gechert, S. (2017). On theories and estimation techniques of fiscal multipliers. *FMM Working Paper, No. 11*, *Hans-Böckler-Stiftung, Macroeconomic Policy Institute (IMK)*, Forum for Macroeconomics and Macroeconomic Policies (FFM), Düsseldorf.

Gechert, S. and Rannenberg, A. (2018). Which fiscal multipliers are regime-dependent? A meta-regression analysis. *Journal of Economic Surveys*, 32(4):1160–1182.

Gonçalves, S. and Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89–120.

Gouriéroux, C., Monfort, A., and Renne, J.-P. (2017). Statistical inference for independent component analysis: Application to structural VAR models. *Journal of Econometrics*, 161(1):111–126.

Grynkiv, G. and Stentoft, L. (2018). Stationary threshold vector autoregresive models. *Journal of Risk and Financial Management*, 11(3):45.

Guerini, M., Moneta, A., Napoletano, M., and Roventini, A. (2020). The janus-facednature of debt: Results from a data-driven cointegrated SVAR approach. *Macroeconomic Dynamics*, 24(1):24–54.

Hall, R. E. (2009). By how much does GDP rise if the government buys more output?Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, 40(2):183–249.

Hansen, B. E. (1996). Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica*, 62(2):413–430.

Hansen, B. E. (1997). Inference in TAR model. *Studies in Nonlinear Dynamics and Econometrics*, 2(1):1–16.

Herwartz, H. (2018). Hodges–Lehmann detection of structural shocks – An analysis of macroeconomic dynamics in the Euro area. *Oxford Bulletin of Economics and Statistics*, 80(4):736–754.

Holland, M., Marçala, E., and de Prince, D. (2020). Is fiscal policy effective in Brazil? An empirical analysis. *The Quarterly Review of Economics and Finance*, 75:40–52.

Hubrich, K. and Teräsvirta, T. (2013). Thresholds and smooth transitions in vector autoregressive models. In *VAR Models in Macroeconomics - New Developments and Applications: Essays in Honor of Christopher A. Sims*, volume 32 of *Advances in Econometrics*, pages 273–326. Emerald Group Publishing Limited.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Laumer, S. and Philipps, C. (2020). Does the government spending multiplier depend on the business cycle? *Available at SSRN: https://ssrn.com/abstract=3699632.*

Lo, M. C. and Zivot, E. (2001). Threshold cointegration and nonlinear effects to the lawof one price.Macroeconomic Dynamics, 5(4):533–576.

López-Vera, A., Pinchao-Rosero, A. D., and Rodríguez-Niño, N. (2018). Non-Linear fiscal multipliers for public expenditure and tax revenue in Colombia. Ensayos sobre Política Económica, 36(85).

Matteson, D. S. and Tsay, R. S. (2017). Independent component analysis via distance covariance. *Journal of the American Statistical Association*, 112(518):623–637.

Michaillat, P. (2014). A theory of countercyclical government multiplier. *American Economic Journal: Macroeconomics*, 6(1):190–217.

Mirdala, R. and Kameník, M. (2017). Effects of Fiscal Policy Shocks in CE3 Countries (TVAR Approach). *Economics and Management*, 20(2):46–64.

Moneta, A., Entner, D., Hoyer, P. O., and Coad, A. (2012). Causal inference by independent component analysis: Theory and applications. *Oxford Bulletin of Economics and Statistics*, 75(5):705–730.

Moneta, A. and Pallante, G. (2020). Identification of structural VAR models via independent component analysis: A performance evaluation study. *LEM Papers Series 2020/24, Laboratory of Economics and Management (LEM)*, *Sant'Anna School of Advanced Studies*, Pisa, Italy.

Mountford, A. and Uhlig, H. (2009). What are the effects of fiscal policy shocks? *Journal of Applied Econometrics*, 24(6):960–992.

Mustea, L. (2015). How large are fiscal multipliers in the US? *Journal of Political Economy*, 20:423–427.

Owyang, M. T., Ramey, V. A., and Zubairy, S. (2013). Are government spending multipliers greater during periods of slack? Evidence from Twentieth-Century historical data. *American Economic Review*, 103(3):129–134.

Perotti, R. (2005). Estimating the effects of fiscal policy in OECD countries. *Centre for Economic Policy Research Discussion Paper 4842.*

Perotti, R. (2007). In search of the transmission mechanism of fiscal policy. *NBER Working Paper No. w13143.*

Ramey, V. A. (2016). Chapter 2 - Macroeconomic shocks and their propagation. In Taylor, J. B. and Uhlig, H., editors, *Handbook of Macroeconomics*, volume 2, pages 71-162. Elsevier.

Ramey, V. A. and Zubairy, S. (2018). Government spending multipliers in good times and in bad: Evidence from US historical data. *Journal of International Money and Finance*, 126(2):850–901.

Restrepo, J. E. and Rincón, H. (2006). Identifying fiscal policy shocks in Chile and Colombia. *Central Bank of Chile, Working paper No. 370*.

Risk, J. N. and Matteson, D. S. (2015). steadyICA: ICA and test of independence via multivariate distance covariance. R Package version 1.0.

Sanches, W. and Galindo, H. (2013). Multiplicadores asimétricos del gasto público y de los impuestos en el Perú. *Ministerio de Economía y Finanzas, Dirección General de Política Macroeconómica.*

Schmidt, J. (2020). Risk, asset pricing and monetary policy transmission in Europe: Evidence from a threshold-VAR approach. *Journal of International Money and Finance*,109:102235.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1):1–48.

Soederhuizen, B., Teulings, R., and Luginbuhl, R. (2019). Estimating the impact of the financial cycle on fiscal policy. *Centraal Planbureau Discussion Paper, CPB Nether-lands Bureau for Economic Policy Analysis*.

Spilimbergo, A., Schindler, M., and Symansky, S. A. (2009). Fiscal multipliers. *IMF Staff Position Note No. 2009/11.*

Székely, G. J. and Rizzo, M. L. (2009). Brownian distance covariance. *Annals of Applied Statistics*, 3(4):1236–1265.

Székely, G. J., Rizzo, M. L., and Bakirov, N. K. (2007). Measuring and testing depen-dence by correlation of distances. *Annals of Statistics*, 36(6):2769–2794.

Tena, J. d. D. and Tremayne, A. (2009). Modelling monetary transmission in UK manufacturing industry. *Economic Modelling*, 26(5):1053–1066.

Tenhofen, J. and Wolff, G. (2007). Does anticipation of government spending matter? Evidence from an expectation augmented VAR. *Discussion Paper Series 1: Economic Studies 2007,14, Deutsche Bundes bank.*

Tsay, R. S. (1998). Testing and modeling multivariate threshold models. *Journal of the American Statistical Association*, 93(443):1188–1202.

Woodford, M. (2011). Simple analytics of the government expenditure multiplier. *American Economic Journal: Macroeconomics*, 3(1):1–35.

Zhang, W., Zhang, Y., Zheng, X., and Zhang, L. (2018). China's fiscal multiplier and its state dependence*. The Manchester School*, 87(2):205–227.

Appendix A GIRF computation

Let $\hat{B}^{(s)}$ be the decomposition matrix of the estimated covariance matrix $\hat{\Sigma}^{(s)}$ for regime s (for instance, a lower triangular Cholesky factor or other matrix that fulfils $\hat{B}^{(s)} \times \left(\hat{B}^{(s)}\right)' = \hat{\Sigma}^{(s)}$). A along the lines of Koop et al. (1996) GIRFs up to an horizon h obtain from the following algorithm:

1. From the estimation of the TVAR model in (1) and (2), get the orthogonal residuals

$$\hat{\varepsilon}_t = \left(\hat{B}^{(s)}\right)^{-1} \hat{u}_t^{(s)}, \ \ t = 1, 2, ..., T$$

2. Sample randomly $h + 1$ error vectors $\hat{\varepsilon}_t$ from step 1, to get a series of random errors $\tilde{V} = (\tilde{\varepsilon}_0, \tilde{\varepsilon}_1, ..., \tilde{\varepsilon}_h)$.
3. Let $z_1, ..., z_T$ be the full sample of data. For a given history $\Omega_{t-1} = z_{t-P}, ..., z_{t-1}$, where P is the model lag order and $t \in \{P + 1, ..., T\}$, expectations in equation (4) can be estimated by

$$E\left(\delta_t, \hat{V}_{t+h}, \Omega_{t-1}\right) = \hat{c}^{(s)} + \sum_{p=1}^{P} \hat{A}_p^{(s)} z_{t-p} + \hat{B}^{(s)} (\tilde{\varepsilon}_0 + \delta_t)$$

and

$$E\left(\hat{V}_{t+h}, \Omega_{t-1}\right) = \hat{c}^{(s)} + \sum_{p=1}^{P} \hat{A}_p^{(s)} z_{t-p} + \hat{B}^{(s)} \tilde{\varepsilon}_0,$$

where $\hat{c}^{(s)}$, $\hat{A}_1^{(s)}, ..., \hat{A}_P^{(s)}$ are the estimated model parameters and δ_t is the shock vector with magnitude δ in the k-th position and zero otherwise.[11] Notice that the initial regime s is defined this way by Ω_{t-1}.

[11] Other ways of implementing the shock can be found in the literature. For example, Batini et al. (2012) replaces the k-th element of the unconditional disturbance vector by or Galvao (2003) suggests to just use t instead of the unconditional disturbance vector. In this regard, we follow the procedure described in Laumer and Philipps (2020).

4. From there, obtain estimations for $E\left(\delta_t, V_{t+h}, \Omega_{t-1}\right)$ and $E\left(V_{t+h}, \Omega_{t-1}\right)$ recursively using the remaining error vectors from $\widetilde{V}$, allowing the process at times, $t + 1, ..., h$ to change the regime if a threshold is crossed.
5. Repeat Steps 3 and 4 for all histories Ω_{t-1} present in the data and take the means for each initial regime s.
6. Repeat Steps 2 to 5 a number of times and take the means for the GIRFs.

Appendix B Data description

As pointed out in the main text, the original data used in the analysis comprises four series spanning from 1990:Q1 to 2019:Q4, corresponding to the three variables used in Blanchard and Perotti (2002) (GDP, government spending and government revenues) plus the interest rate used in a second model as in Allegret and Lemus (2019). GDP at current prices in pesos from year 1996 onward, comes from the Central Bank of Chile database (accessed June 24, 2021); the data was extended to year 1990 by means of year-to-year quarterly GDP growth rates coming from estimates in Correa et al. (2002). Government spending and revenues data come from the DIPRES (Budget Department of the Treasury Ministry) web site, and has been compiled from the Quarterly Operations Reports using government budget information (DIPRES, 1990 to 2019). Following Allegret and Lemus (2019) government taxes has been defined as current income minus transfers, and government expenditures as current expenditures plus capital expenditures. Each of these variables, valued in current Chilean pesos from source, were deflated by the consumer price index (base year 2018) and expressed in per capita terms. The consumer price index with base year 2018 comes from the OECD database (accessed June 24, 2021). Population to year 2019 has been drawn from the World Bank online dataset, annual values were repeatedly applied to each quarter of a specific year. Real per capita GDP, per capita government spending and per capita government revenues have been seasonally adjusted using X13-ARIMA with standard settings. The monetary policy interest rate from year 1995 and onward comes from the Central Bank of Chile public database, the series was extended to year 1990 using reference rates available at https://si3.bcentral.cl/estadisticas/Principal1/Excel/EMF/TASAS/excel.html (accessed June 25, 2021).

Appendix C Intermediate results

Estimated parameters for models 1 and 2 TVARs can be found in table 4. The moduli of maximum eigenvalues of the characteristic polynomials of the estimates VARs are well inside the unit circle (≈0.43 and ≈0.72 conditional on the low- and high-growth regime, respectively, for both models). Normality tests for the estimated error terms can be found in table 5. Finally, estimated covariance matrix decompositions using both, lower triangular and ICA identification strategies are available in tables 6 and 7 for models 1 and 2, respectively.

Table 4. Estimated parameters for the TVAR models 1 and 2

		Model 1			Model 2			
	Parameter	$\Delta log(g_t)$	$\Delta log(y_t)$	$\Delta log(\tau_t)$	$\Delta log(g_t)$	$\Delta log(y_t)$	$\Delta log(\tau_t)$	Δr_t
Low-growth regime	$L.\Delta log(g_t)$	-0.355(0.00)	0.032(0.65)	0.162(0.57)	-0.355(0.00)	0.064(0.39)	0.203(0.50)	0.568(0.84)
	$L.\Delta log(y_t)$	-0.501(0.03)	0.285(0.05)	1.537(0.01)	-0.327(0.17)	0.231(0.12)	1.263(0.04)	10.92(0.06)
	$L.\Delta log(\tau_t)$	-0.001(0.99)	0.013(0.65)	-0.395(0.00)	0.015(0.74)	0.019(0.51)	-0.378(0.00)	1.259(0.25)
	$L.\Delta r_t$	0.018(0.00)	0.004(0.05)	0.002(0.78)	0.007(0.17)	-0.006(0.05)	-0.018(0.15)	0.473(0.00)
	Const.				0.018(0.00)	0.004(0.04)	0.002(0.80)	-0.139(0.07)
High-growth regime	$L.\Delta log(g_t)$	-0.410(0.01)	0.028(0.74)	-0.912(0.03)	-0.408(0.01)	0.006(0.94)	-0.870(0.03)	-8.239(0.01)
	$L.\Delta log(y_t)$	-0.069(0.90)	0.327(0.34)	2.169(0.18)	0.333(0.55)	0.623(0.04)	2.032(0.18)	4.046(0.75)
	$L.\Delta log(\tau_t)$	-0.101(0.06)	0.020(0.52)	-0.363(0.02)	-0.119(0.04)	0.039(0.20)	-0.326(0.04)	0.499(0.69)
	$L.\Delta r_t$	0.020(0.31)	0.010(0.37)	-0.021(0.70)	00000(0.99)	-0.007(0.04)	-0.008(0.61)	0.429(0.00)
	Const.				0.005(0.79)	-0.002(0.85)	-0.017(0.73)	0.123(0.77)

p-values in parentheses

Table 5. Normality tests for the estimated reduced form residuals

	Model 1				Model 2			
Test	Mardia Skewness	Mardia Kurtosis	Henze-Zirkler	Doornik-Hansen	Mardia Skewness	Mardia Kurtosis	Henze-Zirkler	Doornik-Hansen

Low-growth	Statistic	2.935	21.491	0.832	23.732	10.027	43.469	1.403	51.378
	p-val	0.000	0.000	0.376	0.001	0.000	0.000	0.000	0.000
High-growth	Statistic	1.324	14.484	0.749	8.166	3.978	25.445	0.877	16.173
	p-val	0.599	0.787	0.359	0.226	0.143	0.531	0.206	0.040
Pooled VAR	Statistic	1.740	21.838	0.953	29.567	5.478	40.834	1.732	70.493
	p-val	0.000	0.000	0.156	0.000	0.000	0.000	0.000	0.000

Table 6. Structural parameter estimates (multiplied by 100). Model 1

ID Scheme	Regime	Q5	Mean	Q95	Q5	Mean	Q95	Q5	Mean	Q95
Cholesky	Low	2.06	2.64	3.29	0.00	0.00	0.00	0.00	0.00	0.00
		0.08	0.38	0.70	1.33	1.58	1.80	0.00	0.00	0.00
		-3.47	-1.89	-0.28	0.60	1.77	2.96	4.88	5.55	6.22
	High	2.18	2.73	3.28	0.00	0.00	0.00	0.00	0.00	0.00
		-0.79	-0.40	0.03	1.30	1.56	1.79	0.00	0.00	0.00
		-3.85	-1.09	1.72	-1.52	0.96	3.54	5.37	7.24	8.92
ICA	Low	1.31	2.34	3.10	-1.12	0.09	1.06	-2.23	0.14	1.17
		-0.58	0.18	0.77	0.74	1.39	1.79	-0.61	0.29	1.22
		-4.85	-2.23	2.76	-2.88	0.79	3.90	3.69	4.83	5.96
	High	1.61	2.42	3.07	-1.08	0.14	1.01	-1.97	-0.39	1.11
		-1.07	-0.41	0.41	1.06	1.42	1.73	-0.57	0.17	0.88
		-4.77	-0.08	4.38	-3.69	0.13	3.65	4.84	6.78	8.65

Q5 and Q95 refers respectively to the 5th and 95th quantiles from the 500 wild-bootstrap iterations. For further notes see Table 3 in the main text.

Table 7. Structural parameter estimates (multiplied by 100). Model 2

ID	Regime	Q5	Mean	Q95	Q5	Mean	Q95	Q5	Mean	Q95	Q5	Mean	Q95
Cholesky	Low	1.97	2.54	3.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		0.12	0.46	0.79	1.32	1.55	1.78	0.00	0.00	0.00	0.00	0.00	0.00
		-3.57	-1.92	-0.18	0.58	1.75	3.03	4.85	5.53	6.26	0.00	0.00	0.00
		-39.62	-13.60	11.62	-26.62	-14.24	-1.72	-0.92	10.42	20.08	39.94	53.44	69.79
	High	2.24	2.82	3.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		-0.63	-0.27	0.12	1.18	1.44	1.67	0.00	0.00	0.00	0.00	0.00	0.00
		-3.93	-1.13	1.55	-2.08	0.28	2.58	5.36	7.15	8.86	0.00	0.00	0.00
		-21.86	-2.83	16.50	-18.81	-0.15	16.77	6.91	26.31	47.64	36.03	52.36	68.09

ICA	Low	0.99	1.81	2.56	-0.85	0.07	0.92	-0.64	0.31	1.14	-2.92	-0.74	1.10
		-0.41	0.21	0.77	0.74	1.32	1.71	-0.39	0.24	1.17	-1.15	-0.44	0.17
		-4.02	-1.52	1.56	-2.26	0.98	3.98	3.35	4.78	5.97	-1.80	1.00	4.45
		-45.60	3.59	39.81	-32.82	-3.67	16.84	-11.24	2.20	15.05	37.56	51.64	67.21
	High	1.57	2.42	3.07	-0.91	0.32	1.38	-1.61	-0.11	1.35	-1.44	-0.11	1.03
		-0.94	-0.36	0.38	0.82	1.24	1.55	-0.69	0.04	0.76	-0.57	0.02	0.71
		-4.46	-0.42	3.34	-3.64	-0.21	3.23	2.78	5.66	7.88	-2.38	1.90	6.93
		-31.84	1.35	32.64	-25.24	-1.58	22.74	-27.14	9.18	44.16	33.50	51.12	68.18

Q5 and Q95 refers respectively to the 5th and 95th quantiles from the 500 wild-bootstrap iterations. For further notes see Table 3 in the main text.

II. Carbon dioxide atmospheric concentration and hydrometeorological disasters[12]

Abstract

We study the long-run connection between atmospheric carbon dioxide (*CO2*) concentration and the probability of hydrometeorological disasters using a panel of 193 countries over the period 1970-2016 providing annual disaster projections to the year 2040 for each of these countries. Generating accurate predictions on where hydrometeorological disasters have greater chances to occur, may facilitate preparedness and adaption to such disasters, thus helping to reduce their high human and economic costs.

We estimate the probabilities of hydrometeorological disasters at country levels using Bayesian sampling techniques. We decompose the probability of country disaster into the effects of country-specific factors, such as climatological and socio-demographic factors, and factors associated with world climate, which we denote *global probability of disaster* (GPOD). Finally, we subject these GPOD time paths to a cointegration analysis with *CO2* concentration and provide projections to the year 2040 of the GPOD conditional on nine Shared Socioeconomic Pathways scenarios. We detect a stable long-term relation between *CO2* accumulation and the GPOD that allows us to determine projections of the latter process conditional on the former. We conclude that readily available statistical data on global atmospheric concentrations of *CO2* can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of hydrometeorological disasters.

Key words: Hydrometeorological Hazards, Carbon Dioxide, Disaster Forecast, Natural Disasters.

[12] This paper was published in January 2022, in the Web of Science (WOS) journal *Natural Hazards.* See the Annex.

1. Introduction

The United Nations Intergovernmental Panel on Climate Change (IPCC) has concluded that increases in well-mixed greenhouse gas (GHG) concentrations since 1750 are unequivocally caused by human activities and that, as a result of that, it is also unequivocal that human influence has warmed the Earth's atmosphere, ocean and land (IPCC 2014, 2019, 2021). The IPCC states that oceanic and atmospheric temperatures have risen, the overall sea level is higher and Arctic and Antarctic ice and glaciers have diminished, and that, by the year 2050, global warming may reach 1.5°C above pre-industrial levels if the current trend holds (IPCC 2019). Anthropogenic greenhouse gas emissions have increased, leading to atmospheric concentrations of *CO2*, methane and nitrous oxide that are unprecedented in the last 800,000 years, according to the Keeling Curve measurement series made at the Mauna Loa Observatory in Hawaii (USA National Oceanic Atmospheric Administration (NOAA)). As of 2021, for the first time since accurate measurements began 63 years ago, the monthly average of *CO2* concentration in the atmosphere reached 419 parts per million (ppm), and the rate of increase of atmospheric *CO2* accumulation appears to be accelerating (NOAA 2021, 2019a, 2019b).

Evidence of observed weather extremes such as heatwaves, heavy precipitation, droughts, and tropical cyclones, as well as their attribution to human influence has strengthened since the IPCC's Fifth Assessment Report of 2014, and it is likely that extreme precipitation events will intensify and become more frequent in many regions (IPCC 2014, 2021; Baker et al. 2018). This implies that the frequency of natural hazards will also increase, especially those related to flooding, severe weather, and tropical cyclones. In the last two decades there were 3.9 billion people affected by climate disasters, quadrupling the figure of the 1980-1999 period (CRED 2020). According to Mora et al. (2018), by year 2100 each person in the world will be subject to at least one major disaster per year.

No other kind of natural disaster has caused more death and destruction than the hydrometeorological ones (NG 2011). During the past decade, water-related disasters have struck more frequently and more severely, hampering sustainable development by causing political, social, and economic upheaval in many countries (Seung-Soo 2018, NIDM 2019, FEMA 2019, Khan et al. 2019, AON 2019). In fact, hydrometeorological disasters account for 90% of all disasters in terms of people affected. According to the EM-DAT database, in 2018 floods affected 35.4 million people causing 2.859 deaths while 12.8 million people were affected by storms, which caused 1,593 deaths (UNISDR 2019).

To prepare and adapt to hydrometeorological disasters and reduce their high human and economic costs, strategies for managing risks can be developed, including amending land use practices, occupation habits, and economic activities (Ramirez 2011, Herrmann-Lunecke and Villagra 2020, Loebach 2019). A better and more effective use of these strategies could be facilitated by more accurate predictions on where hydrometeorological disasters have greater chances to occur (IPCC 2012, Marvin et al. 2013, Sperling and Szekely 2005, Thomalla et al. 2006, Dore 2003, Cook et al. 2020, Davlasheridze et al. 2017). This explains the large and growing literature attempting to provide better predictions for different climate change induced disasters (Mora et al. 2018, Tan et al. 2019, Wei et al. 2017, 2019, Li and Wang 2018, Pei et al. 2016, Jayawardena 2015, Siverd el al. 2020).

There are several studies predicting characteristics and consequences of future hydrometeorological disasters. However, most of these studies have focused on specific geographical regions (Stott et al. 2004, Otto et al. 2012, Hoerling et al. 2012, Rahmstorf and Coumou 2011, Appendini et al. 2019, Smith et al. 2019, Siverd et al. 2020) or events (Min et al. 2011, Stott et al. 2012, Nuccitelli 2014, Kundzewicz et al. 2014, Arnell and Gosling 2016, Hirabayashi et al. 2013, Herring et al. 2014). Others have applied climate change models to selected episodes, including extreme events (Lee and Lee 2016, Diffenbaugh et al. 2015; Easterling et al. 2000, Pall et al. 2000, Schreider et al. 2000). Most of these studies use climatological models based on physical relationships[13].

The objective of the present work is to study the relationship between atmospheric *CO2* accumulation and hydrometeorological disasters. We study the long-run dynamic and predictive connection between atmospheric carbon dioxide (*CO2*) concentration and the probability of hydrometeorological disasters using a panel of 193 countries over the period 1970-2016. We use a statistical-econometric approach exploiting data evidence for many countries at the same time, an approach which is highly complementary with the more structural and region and/or disaster specific case study approach used by most existing literature. This allows us to: 1. Test the hypothesis that increased atmospheric carbon dioxide accumulation causes more disasters thus giving greater support from a different perspective to the case study literature which has generally found that such causality exists. 2. Provide annual projections of hydro meteorological disasters to the year 2040 for each of the 193 countries that we consider in our analysis. By providing accurate predictions on where hydrometeorological disasters have

[13] Climatological models typically build upon physical principles and laws, fluid mechanics and/or chemistry relations, used for running computer simulations of the earth climate system.

greater chances to occur, we facilitate preparedness and adaption to such disasters, thus helping to reduce their high human and economic costs.

Some recent works have already used the econometric approach, including López et al. (2016, 2020) and Pretis (2020). We add to this body of work, with an approach partly based in López et al. (2020), by using a more flexible methodology that allows us to capture further non linearities by which the link between *CO2* concentration and disaster's incidence may manifest, allowing for better adjustment and more precise estimations. We provide in the first place a quantitative assessment of the long-term relationship between the observed increasing number of hydrometeorological disasters and the concentration of atmospheric *CO2*. A second contribution consists of a predictive tool for this type of disasters that operates at the global level and takes advantage of the long-term relation. We analyze the relationship between the global disaster trends and *CO2* accumulation and use this information to project annual disaster incidences at the country level for nine Shared Socioeconomic Pathways (SSP) scenarios, including the five high-priority scenarios for the Sixth Assessment Report by the IPCC. We demonstrate that generally and readily available statistical data on *CO2* global atmospheric concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of hydrometeorological disasters for each of the 193 countries considered.

The remainder of this work is structured in the following way. Section 2 provides a general overview of the empirical strategy. Section 3 describes the data. Section 4 provides detailed explanations of the empirical approach and estimation results. In section 5, we test for atmospheric *CO2* concentration as a predictor of the global probability of disasters, and then realize projections of (global) disaster probabilities up to 2040. Section 6 concludes. Supplementary Appendices provide data sources and definitions, robustness tests and estimation results in more detail.

2. Empirical strategy

We focus on analyzing the potential of global atmospheric concentration of *CO2* as a meaningful explanatory and predictive factor for the global probability of disasters (GPOD). The key approach is to use a country panel data of disasters to separate country-specific factors from a global common-to-all-countries factor. It is the effect of the latter factor that we expect to be related with the *CO2* concentration.

We assume that risk exposure manifests itself mainly through three contributing factors, local climatic variance, local exposure/vulnerability conditions, and a global climatic pattern. We hypothesize that there is a long-term relationship between the global climatic pattern and *CO2* concentration in the atmosphere. We use *CO2* concentrations as a predictor for hydrometeorological disasters at the global level. In doing so we use panel country-level data covering most countries in the world over the period 1970-2016. We provide statistically valid predictors of the probability of occurrence of climate change induced hydrometeorological disasters at the country level. These predictors can be used by potentially affected countries to design and implement both appropriate and timely risk managing measures and adapting policies.

As our dependent variable is coded after human losses (see Section 3), some considerations are to be taken about the country-specific factors included in the model. Exposure and vulnerability of the population are dependent on country specific characteristics. To control for and then isolate their effects are crucial steps in the identification of the global effect. The key idea is to use proxies for exposure and vulnerability of the population as control variables in the regression analysis. In addition, the use of random country-specific effects allows us to control for other unobserved country effects. This allows us to isolate the effect of factors associated with atmospheric CO2 accumulation free from non-climatic country factors, including exposure and vulnerability.

Socioeconomic, institutional, and demographic factors related to people's vulnerability and exposure to hazards have been highlighted in the works of Tyler and Moench (2012), Banholzer et al. (2014), Hauer et al. (2016), Hallegatte and Rozenberg (2017), Fang et al. (2019) and Mora et al. (2018), among others. Related to the capacity of people to protect themselves against hazards through socioeconomic and institutional factors, we employ GDP per capita as a proxy for population vulnerability. Similarly, we use population density to proxy the exposure of people living in geographic locations prone to be affected by severe hazards. And then the random country effects control for unobserved country-specific factors.

In addition, separation of the country-specific climate effect variance from the total climate effect allows us to obtain the global carbon effect that we are after. As in López et al. (2020), we also consider a set of climate related country-specific variables, that could influence the number and intensity of events beyond the global and long-term local climatic paths, namely annual precipitation, and temperature deviations from their long-term averages. Finally, model flexibility is enhanced using random effects by country, by region and time.

The empirical strategy used can be resumed in the following steps:

1. We estimate the GPOD using an unbalanced annual data panel of 193 countries for the period 1970-2016. To isolate a global (i.e., common-to-all-countries) trend in disaster probabilities as close as possible, we employ: (i) a set of global as well as country-specific covariates (weather conditions, population density and per capita income), (ii) random time effects with flexible resolution (year and decade), and (iii) random effects for the spatial dimension (i.e., country and iso subregion). We apply Bayesian Markov Chain Monte Carlo (MCMC) techniques to estimate a zero-inflated Poisson count data model and use the posterior distributions for sampling model parameters.

2. Samples of the GPOD trends are constructed using the set of posterior parameters obtained in step 1. For this purpose, we only use the subset of common-to-all-countries time-related parameters (e.g., time trends, time effects).

3. The GPOD samples obtained in step 2 are subjected to a cointegration analysis with the atmospheric *log(CO2)*. Two remarks are worth making. First, it is important to investigate if the *log(CO2)* process can be regarded as weakly exogenous in this relationship. Otherwise projections of the GPOD conditional on *log(CO2)* scenarios could be subject to misspecification. Second, as a reflection of global trends in disaster probabilities, our analysis takes suitably account of the causal channel from spatially differentiated climatic patterns to disaster occurrences.

4. We implement projections of the GPOD to the year 2040 conditional on *CO2* under various SSP scenarios. Having the global probability projections, we get back to country-level probabilities by using in-sample mean differences between the GPOD and the country specific estimated probabilities.

Table 1. Summary statistics of the dataset

Variable	Statistic	Complete Sample	Decade 1970	1980	1990	2000	2010	Year 2016
General								
Observations	Total Number of	7516	1127	1402	1727	1930	1330	180
Dependent Variable								
Hydrometeorological disasters	Total number of	4807	272	553	959	1860	1163	166
	Mean per year/country	0.64	0.241	0.394	0.555	0.964	0.874	0.922
	Standard deviation	1.454	0.61	0.952	1.2	1.885	1.8	1.965
Global								
log(CO2)	Mean	5.885	5.802	5.845	5.887	5.936	5.983	6.002
	Standard deviation	0.064	0.011	0.014	0.013	0.016	0.013	-
Δlog(CO2)(annual %)	Mean	0.470	0.374	0.472	0.423	0.504	0.606	0.839
	Standard deviation	0.151	0.169	0.092	0.181	0.100	0.126	-
Local socioeconomic-demographic								
GDP per capita growth (annual %)	Mean per year/country	2.002	2.964	0.970	1.450	2.733	1.931	1.592
	Standard Deviation	6.497	6.312	5.588	8.240	6.547	4.308	3.650
Population density growth (annual %)	Mean per year/country	1.723	2.162	2.097	1.643	1.482	1.408	1.348
	Standard Deviation	1.590	1.326	1.619	1.565	1.740	1.399	1.091
Local climate								
Precipitation deviation (mm/month)	Mean per year/country	-21.141	-18.994	-28.801	-33.130	-12.407	-11.993	-34.491
	Standard Deviation	185.044	150.184	169.295	191.115	181.431	220.537	179.323
Temperature deviation (°C)	Mean per year/country	0.208	-0.043	0.105	0.216	0.278	0.416	0.544
	Standard Deviation	0.450	0.382	0.356	0.393	0.458	0.517	0.543

Note: Data sources are EM-DATA and own calculations

3. The data

The dependent variable is the annual count of hydrometeorological disasters by country and year, i.e., floods and storms[14]. The data on disasters comes from the EM-DAT (EM-DAT: The Emergency Events Database - Université Catholique de Louvain (UCL) - CRED, D. Guha-Sapir

[14] This definition was also adopted by López et al. (2020) and accords with the one by the United Nations Office for Disaster Risk Reduction: “Process or phenomenon of atmospheric, hydrological or oceanographic nature that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage” (UNISDR, 2009).

www.emdat.be).[15] Summary statistics of the dataset can be found in Table 1. An increasing incidence pattern can be observed for hydrometeorological disasters. In fact, over the last two decades there has been an average of almost one disaster per year and country. However, there are many countries which have experienced no disasters for several years. Definition and sources of the data can be found in Appendix A.

4. The count data model for disaster probabilities

Our first goal is to estimate an annual common-to-all-countries factor in disaster occurrence probabilities (i.e., the GPOD) conditional on country-specific climatological, demographic, and socioeconomic characteristics. To do this we first estimate a flexible random effects panel model to subsequently extract the time related GPOD.

The discrete nature of the dependent variable requires the use of a count data model. One issue we must deal with is the excess of zeros present in the dependent variable. As a suitable generalization of a standard Poisson count data model, we rely on a Zero-Inflated Poisson (ZIP) model. The ZIP model formalizes the occurrence of a structural zero with probability π. Moreover, disaster counts exhibit a Poisson distribution with parameter λ. Thus, π corresponds to the structural probability that no disaster occurs, while λ is a parameter associated with the marginal effect of one additional disaster on the estimated probability of disasters. The ZIP model adopted here is structural in the sense that both parameters π and λ depend on covariate information. Let y_{it}, $i = 1, ..., N_t$, $t = 1, ..., T$, denote the number of disasters in country i and time t. Then, the probability of a number y_{it} of disasters to occur is

$$P\left(y_{it}\right) = \pi_{it} I\left(y_{it} = 0\right) + (1 - \pi_{it}) \frac{\lambda_{it}^{y_{it}} e^{-\lambda_{it}}}{y_{it}!}, \tag{1}$$

where $I()$ is an indicator function which equals to one if $y_{it} = 0$. The parameters λ and π are determined by the following link functions,

$$\ln ln \left(\lambda_{it}\right) = c^{(\lambda)} + f_t^{'}\gamma^{(\lambda)} + x_{it}^{'}\beta^{(\lambda)} + \alpha_{1i}^{(\lambda)} + \alpha_{2t}^{(\lambda)} \tag{2}$$

[15] In addition to the EM-DAT coding for the disasters, we also use a more demanding criterion suggested in Thomas et al. (2014) and López et al. (2020) for robustness analysis. Results for this second definition of disasters can be found in Appendix D.

and $\pi_{it} = \frac{B_{it}}{1+B_{it}}$, where $B_{it} = \exp exp\left(c^{(\pi)} + g_t^{'}\gamma^{(\pi)} + z_{it}^{'}\beta^{(\pi)} + \alpha_{1i}^{(\pi)} + \alpha_{2t}^{(\pi)}\right)$, (3)

where $c^{(\lambda)}$ and $c^{(\pi)}$ denote intercept terms, f_t and g_t are vectors of time specific variables, namely t, t^2 and the first differences of *log(CO2)*. The country-specific climatological, demographic, and economic controls enter the linear combinations $x_{it}^{'}\beta^{(\lambda)}$ and $z_{it}^{'}\beta^{(\pi)}$. Apart from measurable heterogeneities, the ZIP model comprises random effects in two dimensions, i.e., geography and time, denoted as $\alpha_{1i}^{(\lambda)}$, $\alpha_{1i}^{(\pi)}$ and $\alpha_{2t}^{(\lambda)}$, $\alpha_{2t}^{(\pi)}$, respectively.[16]

This methodology improves over that in López et al. (2020) in several respects. Firstly, López et al., assume that the global CO2 concentration affects the probability of disasters only through the parameter of the count distribution (in our case the parameter λ) and not through the Bernoulli distribution parameter π. In contrast, our model allows for both parameters to be affected by the GPOD determinants. Secondly, we improve the model adjustment by including linear and quadratic time trends as well as random time effects in two dimensions in both parameter equations, yielding more precise and flexible estimates of the GPOD.

Our methodology, however, implies complex nonlinearities caused by allowing all time-related variables to affect both parameters (λ and π), which make a maximum likelihood estimation approach non reliable. Following Klein et al. (2015), we estimate the model by means of MCMC[17] methods implemented in the software BayesX (Belitz et al. 2012). We performed a total number of 60,000 MCMC iterations. To improve convergence and reduce autocorrelation, we deleted the first 10,000 iterations (burn-in) and stored each 50-th iterate (thinning) leading to a total of 1000 samples. Convergence of the chains has been checked in terms of the sampling paths and autocorrelation plots. We consider effects to be significant if a credibility interval constructed from the posterior 2.5% and 97.5% quantiles of MCMC samples does not include zero.

[16] Iso-region or iso-subregion are used depending on the selected model and refer to a geographical classification of countries. Iso-region corresponds to continent (5 categories total) and iso-subregion to a within continent subdivision (21 categories). For aggregating observations over time, we allow for random year and decade effects.

[17] The Metropolis-Hastings (also known as MCMC) algorithm is a recursive method to simulate multivariate distributions. It can be shown that the simulated distribution converges to the target distribution, a detailed description of the algorithm can be found in Chib and Greenberg (1995). BayesX software utilizes a generalized version of the algorithm with distribution specific iteratively weighted least squares proposal densities.

Table 2. Included explanatory variables in the model with minimal DIC

Parameter	Linear covariates		Random effects	
λ_{it}	f_t	trend trend^2 *Δlog(CO2)*	$\alpha^{(\lambda)}_{2t}$	year decade
	x_{it}	Temperature deviation Precipitation deviation GDP per capita growth Population density growth	$\alpha^{(\lambda)}_{1i}$	country Iso-subregion
π_{it}	g_t	trend *Δlog(CO2)*	$\alpha^{(\pi)}_{2t}$	year decade
	z_{it}	Precipitation deviation	$\alpha^{(\pi)}_{1i}$	country Iso subregion

Note: Parameters and symbols refer to the model in (2) and (3).

For model specification and variable selection, we rely mainly on the deviance information criterion (DIC) (Spiegelhalter et al. 2002). We look for the most flexible and DIC-minimizing specification for both parameters, λ_{it} and π_{it}, in the context of geographic and time related random effects. Table 2 shows the explanatory variables needed to estimate the minimal DIC.

Table 3. Estimated marginal effects on disaster probabilities and ZIP parameters

	$P(y_{it} > 0)$					λ_{it}		π_{it}	
Variable	Mean	SD	Q2.5%	Q50%	Q97.5%	Mean	SD	Mean	SD
Country level									
temperature deviation	-0.005	0.004	-0.012	-0.005	0.003	-0.022	0.018	-	-
precipitation deviation	0.056	0.004	0.047	0.056	0.065	0.167	0.017	-0.074	0.016
GDP per capita growth	0.007	0.004	-0.001	0.007	0.014	0.030	0.018	-	-
population density growth	0.000	0.007	-0.014	0.000	0.013	-0.002	0.031	-	-
Global									

trend	0.163	0.036	0.091	0.165	0.232	0.622	0.165	-0.093	0.044
trend^2	-0.076	0.033	-0.141	-0.074	-0.012	-0.337	0.148	-	-
Δlog(CO2)	0.007	0.005	-0.003	0.007	0.016	0.009	0.021	-0.019	0.010

Notes: SD indicates standard deviations. Q2.5%, Q50% and Q97.5% stand for posterior MCMC quantiles. We regard a parameter as significant, if the zero is not included in the Q2.5% - Q97.5% interval.

Statistics for the estimated marginal effects on $P\left(y_{it} > 0\right)$ (see equation (4) below) and the contribution of each covariate are shown in Table 3 (estimated random effects are not reported because they are too numerous). Precipitation difference from long-term average is significant and implies a 5.6% change in the probability of a disaster per standard deviation[18]. Local temperature deviation appears with insignificant effect. Both the socioeconomic and the demographic controls affects disasters only via the λ equation, and neither exerts a significant effect.[19] It is worth mentioning here that all results for the ZIP model are largely robust for a more restrictive definition of disasters (see Appendix D, Table D3).

We can now estimate the probability of at least one disaster to happen in country i, in year t as

$$P\left(y_{it} > 0\right) = (1 - \hat{\pi}_{it})(1 - e^{-\hat{\lambda}_{it}}), \quad (4)$$

where $\hat{\pi}_{it}$ and $\hat{\lambda}_{it}$ are obtained from (2) and (3) using the MCMC parameter estimates and the estimated random effects.

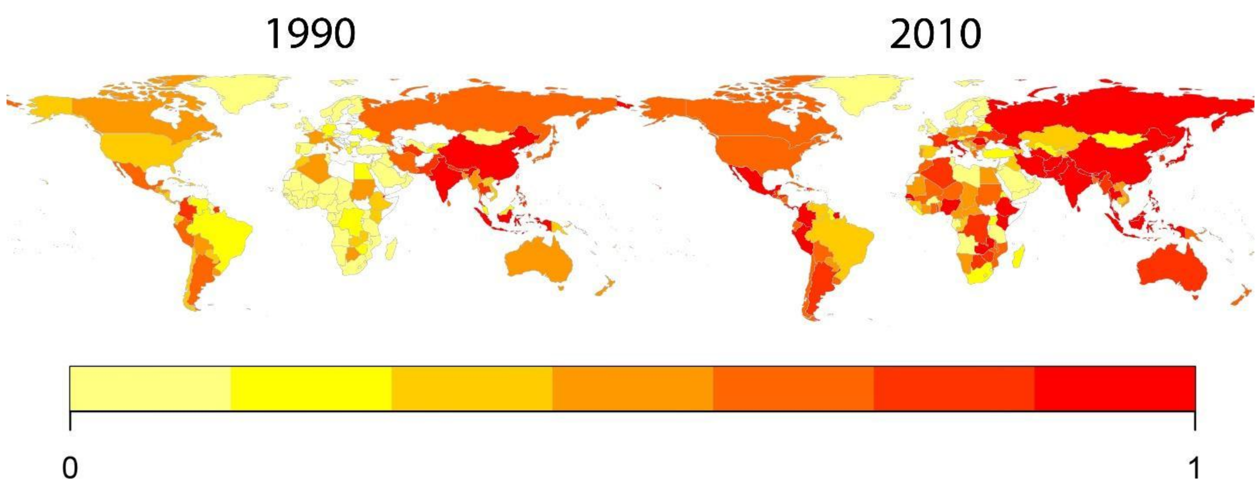
Figure 1 displays the posterior MCMC mean of the estimated probabilities of a disaster by country in years 1990 and 2010 (see Appendix D for a detailed documentation). A concentration

[18] To put the effect estimates into perspective, consider the descriptive statistics in Table 1 using two country examples. Vietnam had a precipitation deviation of 46.74mm/month in 1990 and -78.13 mm/month in 2010; Zambia -81.82 mm/month in 1990 and 37.64 mm/month in 2010. These changes account for -0.67 (Vietnam) and 0.65 (Zambia) standard deviations. Hence, other things equal, this precipitation changes account for a reduction of the probability of at least one disaster by 3.78% for Vietnam, and an increase of 3.62% for Zambia.

[19] As our model selection process favored growth rates instead of log levels for these controls, a direct interpretation of the correlation results in the sense of the ones in Wu et al. (2018), Mora et al. (2018), or López et al (2020) cannot be made here. Taking GDP per capita as an example, we have that on the one hand neoclassical theory suggests conditional higher growth rates for lower income (more vulnerable) countries, while on the other hand growth has been shown to be sensitive to disasters (Loayza et al. 2012, Cavallo et al. 2013 and others). Hence, we refrain from making any causal interpretation.

of disasters in the tropical areas can be observed in 1990, especially in Asia and the Pacific region (see Thomas et al. 2014). A dramatic change occurs in the year 2010 for (almost) all regions. Aligning with earlier findings of increasing disaster incidences (see, for example, Stott et al. 2004, Otto et al. 2012, Hoerling et al. 2012, Rahmstorf and Coumou 2011, Smith et al. 2019, López et al. 2020, Mora et al. 2018), some African countries jump from less than 30% to more than 70% probability of experiencing at least one disaster. In other regions, Russia jumps from a probability of 64% in 1970 to 95% in 2010, U.S.A from 42% to 63%, Australia from 44% to 73% and Brazil from 23% to 40%.

Figure 1. Mean of estimated $P\left(y_{it} > 0\right)$ by country, years 1990 and 2010



5. The GPOD

We are now in position to build GPOD time paths. For this purpose, the effects of all variables that are not explicitly related to time are removed from the computation of the probabilities of interest. Specifically, we construct estimates of $P\left(y_t > 0\right)$ from equation (4) after replacing $\hat{\lambda}_{it}$ and $\hat{\pi}_{it}$, respectively, by

$$\ln ln\left(\hat{\lambda}_t\right) = \hat{c}^{(\lambda)} + f_t^{'}\hat{\gamma}^{(\lambda)} + \hat{\alpha}_{2t}^{(\lambda)} \tag{5}$$

and $\hat{\pi}_t = \frac{\hat{B}_t}{1+\hat{B}_t}$, with $\hat{B}_{it} = \exp exp\left(\hat{c}^{(\pi)} + g_t'\hat{\gamma}^{(\pi)} + \hat{\alpha}^{(\pi)}_{2t}\right).$ (6)

This exercise results in a set of 1,000 time paths samples of GPOD (paths of $P\left(y_t > 0\right)$), which we subject to cointegration and predictive analysis with log (CO2).

5.1 Disaster occurrence probabilities and the atmospheric *CO2* concentration

Let τ_t and q_t denote, respectively, the global time component of estimated probabilities of disasters (the GPODs) and *log(CO2)* in year t. Henceforth we consider q_t as a potential (weakly exogenous) determinant of τ_t. We implement the following regressions which are informative about potential long-run linkages between τ_t and q_t:[20]

$$\tau_t = k_1 + \beta_1 q_t + \omega_{1,t}, \quad (7)$$

$$\Delta\tau_t = k_2 + \alpha_2\tau_{t-1} + \beta_2 q_{t-1} + \omega_{2,t}, \quad (8)$$

and $$\Delta q_t = k_3 + \alpha_3\tau_{t-1} + \beta_3 q_{t-1} + \omega_{3,t}. \quad (9)$$

The variables τ_t and q_t may have a meaningful relation if the estimates of β_1 in (7) are positive for a significant fraction of the performed regressions. The regression model (8) allows for error correcting dynamics inherent in the adjustment of disaster probabilities. Under cointegration and weak exogeneity of q_t, the error correction parameter α_2 must be negative. The regression in (9) is designed to unravel potential violations of weak exogeneity. The process is consistent with weak exogeneity if the parameter α_3 is not significant.

Table 4. Estimated parameters for cointegration analysis

Parameter Regression (7)	Mean	SD	Q2.5%	Q50%	Q97.5%
k_1	-7.110	1.193	-4.909	-7.016	-9.730
β_1	1.241	0.208	1.700	1.226	0.857

[20] See Kremers et al. (1992) for a discussion of single equation cointegration and error-correction models.

R^2	0.849	0.028	0.897	0.851	0.782
Regression (8)					
k_2	-2.299	0.805	-0.895	-2.239	-4.143
α_2	-0.338	0.092	-0.169	-0.34	-0.528
β_2	0.402	0.14	0.724	0.391	0.157
Regression (9)					
k_3	-0.054	0.019	-0.014	-0.054	-0.091
α_3	0.001	0.003	0.007	0.001	-0.004
β_3	0.010	0.003	0.016	0.010	0.003

Note: See Table 3.

Parameter estimates for the cointegration analysis are reported in Table 4. The fact that the estimated parameter β_1 is positive and significant, implies the existence of an equilibrium long-run relationship linking the GPOD and *log(CO2)*. Hence, according to the Engle-Granger theorem (Engle and Granger 1987) the variables are linked by an error-correction mechanism, and at least one of the variables must adjust to transitory violations of the equilibrium relationship. Results from regression (8) show strong evidence that the GPOD adjusts to deviations from the long run equilibrium with the *log(CO2)*.[21] Results from the regression (9) show that α_3 is not significant. This result is consistent with weak exogeneity of *log(CO2)*. Hence, if one of the two variables deviates from their long-term relation, the GPOD adjusts towards a new equilibrium and not the *log(CO2).*[22]

5.2 Projections to year 2040

[21] Under the null hypothesis of no cointegration, testing the significance of 2 requires non-standard critical values (Kremers et al. 1992). Appendix AB.1 provides the results with these values.

[22] We have also applied these exercises to two other related trending variables as placebo, namely Global Temperature and World GDP per capita. Both variables appear to be also correlated in the long-term with the GPOD, but both trending variables fail to be weakly exogenous (see Appendix B.2). Hence, for the conditioning of GPOD projections Global Temperature and World GDP per capita lack an essential qualification.

Both, the diagnosed weak exogeneity of *log(CO2)* and the joint dynamics linking the GPOD and the *log(CO2)* imply a meaningful long term relation between these variables, in which the GPOD values adjust to lagged changes of *log(CO2)*. Although this ‘statistic causality’ is only an observed phenomena capturing the effect of underlaying physical relationships not modeled here, it justifies the use of *log(CO2)* for projections of the GPOD, provided some stability and accuracy tests are confirmed. We can project the GPOD by means of the set of parameters estimated for the regression model (7), using certain assumptions for the conditioning variable (*log(CO2)*),

$$\tau_t = \hat{k}_1 + \hat{\beta}_1 q_t, \qquad (10)$$

where $\hat{k}_1$ and $\hat{\beta}_1$ are the parameters estimated from equation (7), as reported in Table 4. Test results for parameter stability and out-of-sample forecast exercises using the specification in (10) can be found in Appendix B, showing model stability and predictive accuracy.

For performing the conditional projections, we use simulated annual series for *CO2* accumulation up to the year 2040, as provided by Meinshausen et al. (2020) for 9 SSP scenarios.[23] SSPs describe alternative possible evolution pathways in the absence of climate change mitigating policies. Families SSP1 and SSP5 envision relatively optimistic trends, family SSP2 scenarios envision a pathway in which trends continue their historical patterns and SSP3 and SSP4 envision more pessimistic developments (O’Neill et al. 2016).

Figure 2. GPOD projections to year 2040 by SSP scenario with 90% confidence intervals

[23] These scenarios include the five high-priority scenarios for the Sixth Assessment report by the IPCC (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5 and SSP1-1.9), the three scenarios that complete the Tier 2 list suggested by O’Neill et al. (2016) (SSP4-6.0, SSP4-3.4, SSP5-3.4-OS) and a variation of the SSP3-7.0 scenario (Meinshausen et al., 2020). For a comprehensive description of the SSPs we refer the reader to the work of Riahi et al. (2016).

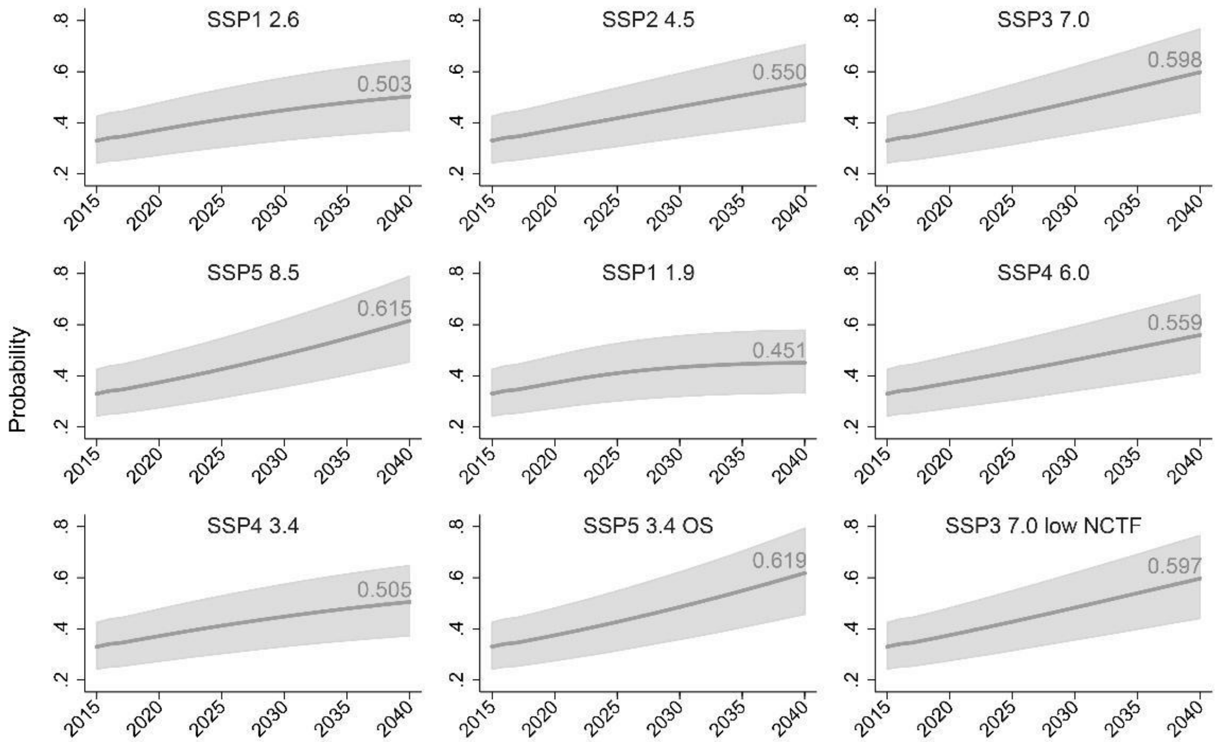


Figure 2 shows GPOD projections to year 2040 by SSP scenario. Except for the more optimistic scenario SSP1-1.9, the rising trend in the GPOD is clear. Comparing results for 2015 and 2040, on average, the time component of global disaster occurrence probabilities can be expected to rise by about 30% or more. The trend is clearly significant since lower bounds of GPOD confidence intervals for the year 2040 are above the mean projections for the year 2015.

While the GPOD projections reflect the global impact of the expected increases of atmospheric *CO2* concentration, the projections are not directly informative for country-specific disaster probabilities. Thus, to provide global maps of probabilities of at least one disaster per annum to occur by country in 2040, we combine the projected GPOD with in-sample country-specific average relations between the estimates of $P\left(y_{it} > 0\right)$ and the GPOD (i.e., $P\left(y_{t} > 0\right)$).

Figure 3. Mean of projected $P\left(y_{it} > 0\right)$ in year 2040 for Tier 1 scenarios

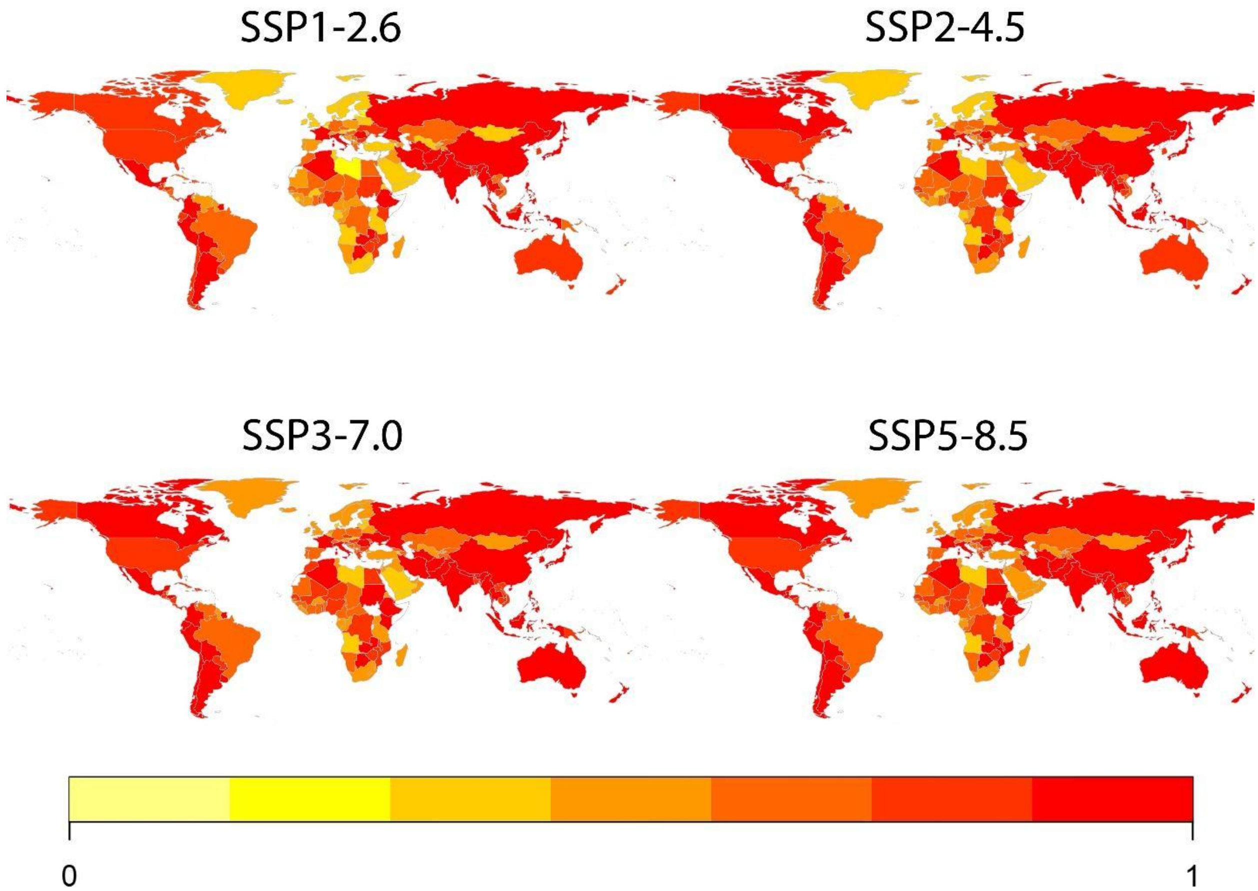


Figure 3 displays the estimated country-specific probabilities of having at least one disaster per year for the four Tier 1 priority scenarios (O'Neill et al. 2016) and allows for a direct comparison with results displayed in Figure 1 (see Appendix E for a detailed documentation). Probabilities of disasters to occur by country are subject to marked increases. For most countries, the probabilities to experience at least one disaster in 2040 are above 50%. Most Asian countries can be expected to experience at least one disaster per year more frequently in 2040 than 2010 under all displayed scenarios. Austria jumps from a 14.5% probability of experiencing at least one disaster in 2010 to 39.7% in 2040 under SSP1-2.6 scenario and to 50.9% under SSP5-8.5 scenario, Congo from 32% to 47% under SSP1-2.6 and 58.3% under SSP5-8.5, Guinea from 28.6% in 2010 to 56.9% in 2040 under SSP1-2.6 and 68.2% under SSP5-8.5, Lebanon from 5.8% in 2010 to 41.7% in 2040 under SSP5-8.5, Singapore from 46% to 61.9% under SSP1-2.6, United Kingdom from 8.6% to 37.8% under SSP1-2.6, and so on.

These projections by country can be an important input for governments and communities to design and develop adequate strategies to face upcoming hydrometeorological disasters. The complete data set of projected probabilities for any of the countries considered in this analysis, from year 2021 to 2040, for the 9 scenarios considered, are available upon request from the authors.

9. Conclusion

This study adds to a new literature using the statistics/econometric approach to study the connection between climate change and natural disasters. We have quantitatively studied the long-run dynamic and predictive connection between atmospheric *CO2* accumulation and the probability of hydrometeorological disaster occurrence. As stated by the IPCC, other international agencies as well as by numerous authors, this could contribute to a more effective and less costly use of preventive and mitigating instruments to reduce people's exposure and vulnerability.

To discover the properties of *CO2* accumulation measures as a predictive tool for hydrometeorological disasters, we have employed flexible Bayesian MCMC simulation techniques to first obtain a global trend in the probabilities of disaster occurrence, conditional on climate, socioeconomic and other country-specific factors. We then analyzed its relationship with *CO2* levels to assess and check the ability of the trend in global atmospheric *CO2* concentration to accurately anticipate the future occurrence of hydrometeorological disasters. Finally, we used this information to forecast disaster incidences at the global level as well as for each of the countries considered in the analysis, using high-priority scenarios as reported by the Sixth Assessment Report of the IPCC.

We show that statistical data on global atmospheric *CO2* concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of hydrometeorological disasters. Moreover, we also show that controlling for country-specific characteristics, and conditional on emission scenarios, most countries will be affected by at least one annual disaster with a 50% or higher probability by the year 2040.

References

AON (2019) Weather, climate, and catastrophe insight: 2018 annual report. AON Empower Results. http://thoughtleadership.aonbenfield.com/Documents/20190122-ab-if-annual-weather-climate-report-2018.pdf.

Appendini CM, Meza-Padilla R, Abud-Russell S et al. (2019) Effect of climate change over landfalling hurricanes at the Yucatan Peninsula. Clim. Change 157:469–482. https://doi.org/10.1007/s10584-019-02569-5

Arnell NW, Gosling SN (2016) The impacts of climate change on river flood risk at the global scale. Clim Change. 134(3):387-401. https://doi.org/10.1007/s10584-014-1084-5

Baker H, Millar R, Karoly D, Beyerle U, Guillod B, Mitchell D, Shiogama H, Sparrow S, Woolings T, Allen M (2018) Higher *CO2* concentrations increase extreme event risk in a 1.5 °C world. Nature Clim Change 8:604–608. https://doi.org/10.1038/s41558-018-0190-1

Banholzer S, Kossin J, Donner S (2014) The impact of climate change on natural disasters. In: A. Singh and Z. Zommers (eds) Reducting Disasters: Early Warning Systems for Climate Change. Springer. pp 21-49.

Belitz C, Brezger A, Kneib T, Lang S, Umlauf N (2012) BayesX. Software for Bayesian inference in structured additive regression models. Version 2.1. Available from http://www.bayesx.org.

Cavallo E, Galiani S, Noy I, Pantano J (2013) Catastrophic Natural Disasters and Economic Growth. Rev Econ Stat 95(5). pp.1549-1561. https://doi.org/10.1162/REST_a_00413

Chib S, Greenberg E (1995) Understanding the Metropolis-Hastings algorithm. Am Stat 49(4):327-335. https://doi.org/10.2307/2684568

Cook LM, McGinnis S, Samaras C (2020) The effect of modeling choices on updating intensity-duration-frequency curves and stormwater infrastructure designs for climate change. Clim Change 159:289-308. https://doi.org/10.1007/s10584-019-02649-6

CRED (2020) Human Costs of Disasters: An overview of the last 20 years. Centre for Research on the Epidemiology of Disasters (CRED). https://geographyandyou.com/human-cost-of-disasters-2000-2019/

Davlasheridze M, Fisher-Vanden K, Klaiber AH (2017) The effects of adaptation measures on hurricane induced property losses: Which FEMA investments have the highest returns? J Environ Econ Manag 81:93-114. https://doi.org/10.1016/j.jeem.2016.09.005

Diffenbaugh NS, Swain DL, Touma D (2015) Anthropogenic warming has increased drought risk in California. PNAS. 112(13):3931-3936. https://doi.org/10.1073/pnas.1422385112

Dore MHI (2003) Forecasting the Conditional Probabilities of Natural Disasters in Canada as a Guide for Disaster Preparedness. Nat Hazards. 28(2):249-269. https://doi.org/10.1023/A:1022978024522

Easterling DR, Meehl GA, Parmesan C, Changnon SA, Karl TR, Mearns LO (2000) Climate extremes: Observations, modeling, and impacts. Science. 289(5487):2068-2074. https://doi.org/10.1126/science.289.5487.2068

Engle R, Granger C (1987) Co-Integration and error correction: Representation, estimation and testing. Econometrica. 55:251-276. https://doi.org/10.2307/1913236

Fang J, Lau CK, Lu Z, Wu W, Zhu L (2019) Natural disasters, climate change and their impact on inclusive wealth in G20 countries. Environ Sci Pollut Res 26(2):1455-1463. https://doi.org/10.1007/s11356-018-3634-2

FEMA (2019) The national flood insurance program. Federal Emergency Management Agency, US Department of Home Security, USA. https://www.fema.gov/flood-insurance

Hallegatte S, Rozenberg J (2017) Climate change through a poverty lens. Nat Clim Change 7:250-256. https://doi.org/10.1038/nclimate3253

Hauer ME, Evansand JM, Mishra DR (2016) Millions projected to be at risk from sea-level rise in the continental United States. Nat Clim Change 6:691-695. https://doi.org/10.1038/nclimate2961

Herring SC, Hoerling MP, Peterson TC, Stott PA (2014) Explaining extreme events of 2013 from a climate perspective. Bull Am Meteorol Soc 95(9): S1-S104. https://doi.org/10.1175/1520-0477-95.9.S1.1

Herrmann-Lunecke MG, Villagra P (2020) Community resilience and urban planning in tsunami prone settlements: the case of Mehuin, Queule, Toltén and Puerto Saavedra, Chile. Disasters 44(1):103-124. https://doi.org/10.1111/disa.12369

Hirabayashi Y, Mahendran R, Koirala S, Konoshima L, Yamazaki D, Watanabe S, Kim H, Kanae S (2013) Global flood risk under climate change. Nat Clim Change. 3:816-821. https://doi.org/10.1038/nclimate1911

Hoerling M, Eischeid J, Perlwitz Q, Zhang JXT, Pegion P (2012) On the increased frequency of Mediterranean drought. J Clim 25(6):2146-2161. https://doi.org/10.1175/JCLI-D-11-00296.1

IPCC (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA.

IPCC (2014) Climate change 2014: Synthesys report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the International Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A.Meyer (eds.)]. IPCC, Geneva, Switzerland.

IPCC (2019) IPCC Special Report on the Ocean and Cryosphere in a Changing Climate. Intergovernmental Panel on Climate Change. https://www.ipcc.ch/site/assets/uploads/sites/3/2019/12/SROCC_ FullReport_FINAL.pdf

IPCC (2021) Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. In Press. https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Full_Report.pdf

Jayawardena AW (2015) Hydro-meteorological disasters: Causes, effects and mitigation measures with special reference to early warning with data driven approaches of forecasting. Procedia IUTAM. 17:3-12. https://doi.org/10.1016/j.piutam.2015.06.003

Khan K, Zaman K, Shoukry A, Sharkawy A, Gani S, Sasmoko S , Ahmad J, Khan A, Sanil H (2019) Natural disasters and economic losses: Controlling external migration, energy and environmental resources, water demand, and financial development for global prosperity. Environ Sci Pollut Res 26:14287-14299. https://doi.org/10.1007/s11356-019-04755-5

Klein N, Kneib T, Lang S (2015) Bayesian generalized additive models for location, scale and shape zero-inflated and overdispersed count data. J Am Stat Assoc 110(509):405-419. https://doi.org/10.1080/01621459.2014.912955

Kremers JJM, Ericsson N, Dolado JJ (1992) The Power of Cointegration Tests. Oxf Bull Econ Stat 54(3):325-48. https://doi.org/10.1111/j.1468-0084.1992.tb00005.x

Kundzewicz ZW, Kanae S, Seneviratne SI, Handmer J, Nicholls N, Peduzzi P, Mechler R, Bouwer LM, Arnell N, Mach K, Muir-Wood R, Brakenridge GR, Kron W, Benito G, Honda Y, Takahashi K, Sherstyukov B (2014) Flood risk and climate change: Global and regional perspectives. Hydrol Sci J 59(1):1-28. https://doi.org/10.1080/02626667.2013.857411

Lee WS, Lee MI (2016) Interannual variability of heat waves in South Korea and their connection with large-scale atmospheric circulation patterns. Int J Climatol 36(15):4815-4830. https://doi.org/10.1002/joc.4671

Li J, Wang B (2018) Predictability of summer extreme precipitation days over eastern China. Clim Dyn 51:4543–4554. https://doi.org/10.1007/s00382-017-3848-x

Loayza N, Olaberría E, Rigolini J, Christiansen L (2012) Natural Disasters and Growth: Going Beyond the Averages. World Dev 40(7):1317-1336. https://doi.org/10.1016/j.worlddev.2012.03.002

Loebach P (2019). Livelihoods, precarity, and disaster vulnerability: Nicaragua and Hurricane Mitch. Disasters 43(4):727-751. https://doi.org/10.1111/disa.12402

López R, Thomas V, Troncoso P (2016) Economic growth, natural disasters, and climate change: New empirical estimates. Series Documentos de Trabajo No. 434, pp. 1 - 38. http://repositorio.uchile.cl/handle/2250/143427

López R, Thomas V, Troncoso P (2020) Impacts of carbon dioxide emissions on global hydro meteorological disasters. Clim Dis Dev J 4(1):30-50. https://doi.org/10.18783/cddj.v004.i01.a03

Marvin HJP, Kleter GA, Van der Fels-Klerx HJ, Noordam MY, Franz E, Willems DJM, Boxall B (2013) Proactive systems for early warning of potential impacts of natural disasters on food safety: Climate-change-induced extreme events as case in point. Food Control 34(2):444-456. https://doi.org/10.1016/j.foodcont.2013.04.037

Meinshausen M, Nicholls Z R J, Lewis J, Gidden M J, Vogel E, Freund M, Beyerle U, Gessner C, Nauels A, Bauer N, Canadell J G, Daniel J S, John A, Krummel P B, Luderer G, Meinshausen N, Montzka S A, Rayner P J, Reimann S, Smith S J, van den Berg M, Velders G J

M, Vollmer M K, Wang R H J (2020) The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. Geosci Model Dev 13(8):3571–3605, https://doi.org/10.5194/gmd-13-3571-2020

Min SK, Zhang X, Zwiers FW, Hegerl GC (2011) Human contribution to more-intense precipitation extremes. Nature 470:378-381. https://doi.org/10.1038/nature09763

Mora C, Spirandelli D, Franklin EC, et al. (2018) Broad threat to humanity from cumulative climate hazards intensified by greenhouse gas emissions. Nat Clim Change 8:1062–1071. https://doi.org/10.1038/s41558-018-0315-6

NG (2011) Floods 101. National Geographic. https://www.youtube.com/watch?v=4PXj7bOD7IY

NIDM (2019) Hydro-Meteorological Disasters. National Institute of Disaster Management, Ministry of Home Affairs, Government of India. https://nidm.gov.in/PDF/Disaster hymet.pdf

NOAA (2019a) Carbon dioxide levels hit record peak in May. National Oceanic and Atmospheric Administration, U.S. Department of Commerce. https://research.noaa.gov/article/ArtMID/587/ArticleID/2461/Carbon-dioxide-levels-hit-record-peak-in-May

NOAA (2019b) Global carbon dioxide growth in 2018 reached 4th highest on record. National Oceanic and Atmospheric Administration, U.S. Department of Commerce. https://www.noaa.gov/news/global-carbon-dioxide-growth-in-2018-reached-4th-highest-on-record

NOAA (2021) Carbon dioxide peaks near 420 parts per million at Mauna Loa observatory**.** National Oceanic and Atmospheric Administration, U.S. Department of Commerce. https://research.noaa.gov/article/ArtMID/587/ArticleID/2764/Coronavirus-response-barely-slows-rising-carbon-dioxide

Nuccitelli D (2014) California just had its worst drought in over 1200 years, as temperatures and risks rise. The Guardian. https://www.theguardian.com/environment/climate-consensus-97-per-cent/2014/dec/08/california-just-had-its-worst-drought-in-over-1200-years Accessed 05 May 2021

O'Neill B C, Tebaldi C, van Vuuren D P, Eyring V, Friedlingstein P, Hurtt G, Knutti R, Kriegler E, Lamarque J-F, Lowe J, Meehl G A, Moss R, Riahi K, Sanderson, B M (2016) The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. Geosci Model Dev 9:3461–3482. https://doi.org/10.5194/gmd-9-3461-2016

Otto FE, Massey N, Van Oldenborgh GJ, Jones RG, Allen MR (2012) Reconciling two approaches to attribution of the 2010 Russian heat wave. Geophys Res Lett. 39(4):L04702. https://doi.org/10.1029/2011GL050422

Pall P, Aina T, Stone DA, Nozawa T, Hilberts AGJ, Lohmann D, Allen MR (2000) Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature 470:382-385. https://doi.org/10.1038/nature09762

Pei L, Xia J, Yan Z, Yang H (2016) Assessment of the Pacific decadal oscillation's contribution to the occurrence of local torrential rainfall in north China. Clim Change 144:391-403. https://doi.org/10.1007/s10584-016-1610-8

Pretis, F (2020) Econometric modelling of climate systems: The equivalence of energy balance models and cointegrated vector autoregressions. J Econom. 214(1):256-273. https://doi.org/10.1016/j.jeconom.2019.05.013

Rahmstorf S, Coumou D (2011) Increase of extreme events in a warming world. Proc Natl Acad Sci USA 108(44):17905-17909. https://doi.org/10.1073/pnas.1101766108

Ramírez F (2011) Resettlement as a preventive measure in a comprehensive risk reduction framework. In E. Correa, F. Ramírez, and A. Sanahuja (eds) Populations at Risk of Disaster. World Bank and Global Facility for Disaster Reduction and Recovery, Washington, DC. pp 15-27.

Riahi K, van Vuuren D P, Kriegler E, Edmonds J, O'Neill B C, Fujimori S, Bauer N, Calvin K, Dellink R, Fricko O, Lutz W, Popp A, Crespo Cuaresma J, KC S, Leimbach M, Jiang L, Kram T, Rao S, Emmerling J, Ebi K, Hasegawa T, Havlik P, Humpenöder F, Aleluia Da Silva L, Smith S, Stehfest E, Bosetti V, Eom J, Gernaat D, Masui T, Rogelj J, Strefler J, Drouet L, Krey V, Luderer G, Harmsen M, Takahashi K, Baumstark L, Doelman J, Kainuma M, Klimont Z, Marangoni G, Lotze-Campen H, Obersteiner M, Tabeau A, Tavoni M (2016) The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An Overview. Glob Environ Change. 42: 153-168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Schreider S Y, Smith DI, Jakeman AJ (2000) Climate change impacts on urban flooding. Clim Change 47(1):91-115. https://doi.org/10.1023/A:1005621523177

Seung-Soo H (2018) Water and disasters. In TOPICS Geo Natural Catastrophes 2017: Analyses, Assessments, Positions. Münchener Rückversicherungs-Gesellschaft Königinstrasse 107, 80802 München, Germany: Munich Re. pp 36-37.

Siverd C, Hagen S, Bilskie M, Braud D, Twilley R (2020) Quantifying storm surge and risk reduction costs: a case study for Lafitte, Louisiana. Clim Change 161:201-223. https://doi.org/10.1007/s10584-019-02636-x

Smith A, Bates PD, Wing O, Sampson C, Quinn N, Neal J (2019) New estimates of flood exposure in developing countries using high-resolution population data. Nat Commun 10(1814). https://doi.org/10.1038/s41467-019-09282-y

Sperling F, Szekely F (2005) Disaster risk management in a changing climate, vulnerability and adaptation. Discussion paper prepared for the world conference on disaster reduction - reprint with addendum on conference outcomes. Vulnerability and Adaptation Resource Group, Washington, DC.

Spiegelhalter DJ, Best NG, Carlin BP, van der Linde V (2002) Bayesian measures of model complexity and fit. J R Stat Soc B 64(4):583-639. https://doi.org/10.1111/1467-9868.00353

Stott P, Allen M, Christidis N, Dole R, Hoerling M, Huntingford C, Pall P, Perlwitz J, Stone D (2012) Attribution of weather and climate-related events. In Climate Science for Serving Society. Springer, Netherlands. pp 307-337.

Stott P, Stone DA, Allen M (2004) Human contribution to the European heatwave of 2003. Nature 432:610-614. https://doi.org/10.1038/nature03089

Tan K, Huang P, Liu F, Murakami H, Hsu P (2019) Simulated ENSO's impact on tropical cyclone genesis over the western North Pacific in CMIP5 models and its changes under global warming. Int J Climatol 39:3668-3678. https://doi.org/10.1002/joc.6031

Thomalla F, Downing T, Spanger-Siegfried E, Han G, Rockstrom J (2006) Reducing hazard vulnerability: towards a *common* approach between disaster risk reduction and climate adaptation. Disasters 30(1):39-48. https://doi.org/10.1111/j.1467-9523.2006.00305.x

Thomas V, Albert J, Hepburn C (2014) Contributors to the frequency of intense climate disasters in Asia-Pacific countries. Clim Change 126(3-4):381-398. https://doi.org/10.1007/s10584-014-1232-y

Tyler S, Moench M (2012) A framework for urban climate resilience. Clim Dev 4(4):311-326. https://doi.org/10.1080/17565529.2012.745389

UNISDR (2009) United Nations Office for Disaster Risk Reduction. Terminology on disaster risk reduction.

UNISDR (2019) United Nations Office for Disaster Risk Reduction. Press release: EMBARGO 11.00 CET, JANUARY 24.

Wei W, Yan Y, Jones PD (2017) Potential Predictability of Seasonal Extreme Precipitation Accumulation in China. J Hydrometeorol 18(4):1071-1080. https://doi.org/10.1175/JHM-D-16-0141.1

Wei W, Yan Y, Jones PD (2019) A decision-tree approach to seasonal prediction of extreme precipitation in eastern China. Int J Climatol 40(1):255-272. https://doi.org/10.1002/joc.6207

Wu J, Han G, Zhou H, Li N (2018) Economic development and declining vulnerability toclimate-related disasters in China. Environ Res Lett 13:034013. https://doi.org/10.1088/1748-9326/aaabd7

Appendix A Data definitions and sources

In what follows we provide sources and definition for the covariates used in the analysis.

As mentioned in the main text, the dependent variable is the annual count of hydrometeorological disasters by country and year, i.e., floods and storms. The EM-DAT criterion for coding a natural event as a disaster is that it fulfills at least one of the following conditions: 10 or more people dead, 100 or more people affected, declaration of state of emergency or a call for international assistance was given. Thomas et al. (2014) have suggested more demanding conditions, i.e., 100 or more people dead or 1000 or more people affected (see also Lopez et al. 2020), since such a more exigent criterion is less likely to suffer from underreporting bias. We use this second definition for robustness tests, results can be found in Appendix D below.

The set of demographic (population density growth) and economic (GDP per capita growth) variables used as proxies for population's exposure and vulnerability were drawn from the World Development Indicators published by the World Bank.

CO2 data was drawn from the NOAA\ESRL Global Monitoring Division (Dr. Pieter Tans, NOAA/ESRL (www.esrl.noaa.gov/gmd/ccgg/trends/) and Dr. Ralph Keeling, Scripps Institution of Oceanography (scrippsco2.ucsd.edu/)).

Annual precipitation and temperature means by country were obtained from monthly grid geographical data. We first obtained annual averages from monthly measures for each grid point in the original datasets. Then we built geographical quadrants for each country using information on maximum and minimum latitude and longitude boundaries[24], to finally take the mean of all grid points within these quadrants. Precipitation data was drawn from the Global Precipitation Climatology Centre (GPCC) database[25], and temperature data was obtained from the HadCRUT4 global temperature dataset[26]. Prior to model estimation, all explanatory variables have been standardized. Hence, the interpretation of marginal results should be made in terms of standard deviations.

[24] Each boundary was expanded by half the distance between two grid data points, to assure that small countries (e.g. San Marino) had at least one point associated.

[25] Full Data Monthly Product Version 2018, 1°x1° grid resolution monthly land surface precipitation information (Schneider et al. 2018).

[26] 5°x5° grid resolution (Morice et al. 2012).

Appendix B Cointegration analysis robustness tests

This appendix provides some alternative results for the cointegration exercise in section 5.1.

B.1 Significance tests for equation (9) using non-standard critical ratios

Equation (9) in the main text allows for error correcting mechanisms:

$$\Delta\tau_t = k_2 + \alpha_2\tau_{t-1} + \beta_2 q_{t-1} + \omega_{2,t} \qquad (9)$$

Where τ stands for the GPOD and q for l*og(CO_2).* Noting under the null hypothesis of no cointegration testing the significance of $\alpha_2$requires non-standard critical values, we check if sampled estimates of α_2 are less than zero for a significant fraction of the 1000 performed regressions. Moreover, we evaluate how often single equation *t*-ratios for α_2 are below a non-standard 5% critical value of -3.3. Confirming the strong evidence against the hypothesis of `no cointegration', 15.6% of the *t*-ratios of α_2 are smaller than a 5% critical value of -3.3.

B.2 Cointegration analysis using global temperature and World GDP per capita

Following López et al. (2020), in analogy to Table 4 in the main text, Tables B1 and B2 below show cointegration parameter estimates using alternative Climate Change related variables, namely *log(Global temperature)* and *log(World GDP pc)* instead of *log(CO_2)*, respectively, as potential (weekly exogenous) determinants (q_t) of the GPOD (τ_t) in equations (7), (8) and (9) (see Section 5.1 in the main text).

Both trending variables (*log*) world GDP per capita and global temperature exhibit a long-term relation with the GPOD (β_1 is positive and significant for both sets of regressions). For both variables, *log(global temp)* and *log(World GDP pc)*, however, positivity of parameter estimates for α_3 in regression (9) implies that these variables adjust to deviations of τ_t (the GPOD) from the long-term equilibrium. Hence, these variables cannot be regarded as weakly exogenous, and are prone to obtain biased GPOD projections if used as conditional information.

Table B1. Estimated parameters for cointegration analysis using global temperature

Parameter	Mean	SD	Q2.5%	Q50%	Q97.5%
Regression (7)					
k_1	-10.814	1.817	-7.582	-10.664	-14.749
β_1	4.129	0.693	5.639	4.072	2.896
R^2	0.768	0.030	0.819	0.771	0.700
Regression (8)					
k_2	-1.502	0.879	0.013	-1.449	-3.378
α_2	-0.172	0.067	-0.050	-0.167	-0.304
β_2	0.578	0.335	1.292	0.557	0.001
Regression (9)					
k_3	1.259	0.164	1.583	1.251	0.944
α_3	0.092	0.020	0.139	0.090	0.060
β_3	-0.478	0.062	-0.358	-0.476	-0.601

Note: SD indicates standard deviations. Q2.5%, Q50% and Q97.5% stand for posterior MCMC quantiles. We regard a parameter as significant if the zero is not included in the Q2.5% - Q97.5% interval.

Table B2. Estimated parameters for cointegration analysis using World GDP per capita

Parameter	Mean	SD	Q2.5%	Q50%	Q97.5%
Regression (7)					
k_1	-3.355	0.563	-2.322	-3.314	-4.579
β_1	0.398	0.066	0.544	0.393	0.276
R^2	0.858	0.027	0.905	0.860	0.794
Regression (8)					
k_2	-1.117	0.387	-0.434	-1.088	-1.980
α_2	-0.351	0.095	-0.179	-0.352	-0.541
β_2	0.133	0.046	0.236	0.130	0.053
Regression (9)					
k_3	0.365	0.113	0.594	0.359	0.156

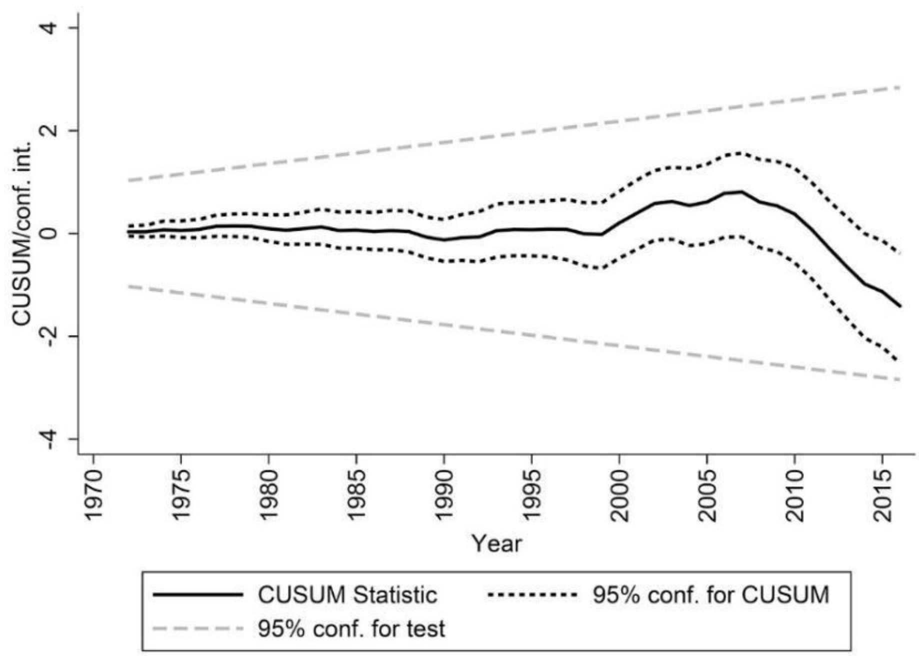
α_3	0.089	0.036	0.167	0.085	0.025
β_3	-0.041	0.013	-0.016	-0.040	-0.068

Note: See Table B1.

Appendix C Diagnostics of the predictive properties of *log(CO_2)* for the GPOD

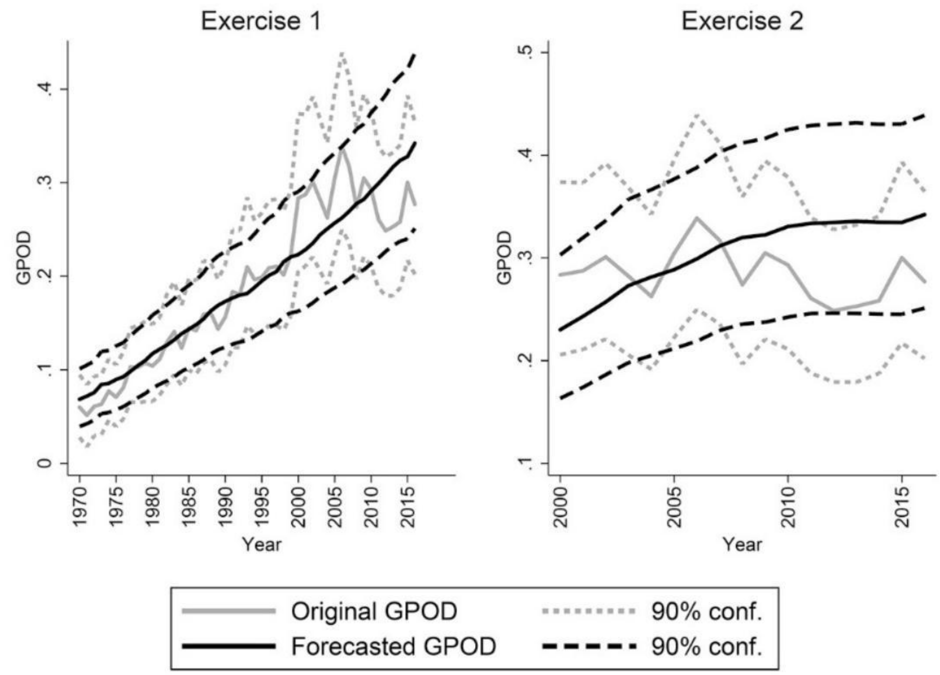
In this section we implement a series of out-of-sample forecast exercises to inspect the potential of *log(CO_2)* as a predictor for the GPOD. The specification used for all pseudo predictive analysis is based on the static regression model (7) and stated in equation (10) in the main text.

Figure C1. CUSUM statistics for the parameters in equation (10)



The static regression model would be unsuitable for a conditional predictive analysis if it suffers from structural instability. Therefore, we first investigate parameter stability by means of CUSUM statistics. Figure C1 displays the outcomes from the set of 1000 CUSUM profiles joint with the corresponding critical values. As a result, we cannot reject the null hypothesis of parameter stability with 5% significance.

Figure C2. Forecast exercises results (left: leave one out; right: recursive analysis starting in 2000)



Since the parameters in equation (10) are stable, we can use it for predicting GPOD trends τ_t conditional on information about *log(CO₂),* i.e., q_t. We perform two exercises to assess the accuracy of such predictions in a pseudo out-of-sample context. On the one hand, we adopt so-called `leave one out' regressions for parameter estimation and subsequent prediction of the left-out observation τ_t conditional on the left-out information about q_t. On the other hand, we perform sequential one-step ahead predictions in a recursive manner starting with initial samples covering the period from 1970 until 1999. For both exercises, we consider a forecasted probability curve as a good fit, if the mean of the original probabilities is covered by the 90% confidence interval of the forecasted one. Respective results are displayed in Figure C2. As can be seen in both panels of Figure C2, our criteria for acceptable forecasts are met throughout.

Appendix D Results for a more stringent codification of hydrometeorological disasters

In this appendix we redo the analysis described in Sections 4 and 5.1 adopting the more stringent classification of disasters used by Thomas et al. (2014) and López et al (2020). Tables D1, D2, D3 and D4 show statistics and results for this second category of disasters, which are analogous to the results and statistics in Tables 1, 2, 3 and 4 in the main text, respectively. As it can be seen, all results are qualitatively similar to those reported in the main text in terms of order of magnitude and effect directions.

Table D1. Summary statistics of hydrometeorological disasters (more demanding coding)

Variable	Statistic	Complet e Sample	Decade 1970	1980	1990	2000	2010	Year 2016
Dependent Variable								
Hydrometeorological disasters	Total number of	3185	178	353	624	1204	826	110
	Mean per year/country	0.424	0.158	0.252	0.361	0.624	0.621	0.611
	Standard deviation	1.068	0.486	0.714	0.846	1.375	1.359	1.500

Note: Data source is EM-DAT

Table D2. Included explanatory variables in the model with minimal DIC

Parameter	Linear Covariates		Random Effects	
λ_{it}	f_t	trend trend^2 *Δlog(CO2)*	$\alpha_{2t}^{(\lambda)}$	year decade
	x_{it}	Temperature deviation Precipitation deviation GDP per capita growth Population density growth	$\alpha_{1i}^{(\lambda)}$	country isosubregion
π_{it}	g_t	trend *Δlog(CO_2)*	$\alpha_{2t}^{(\pi)}$	decade
	z_{it}	Precipitation deviation	$\alpha_{1i}^{(\pi)}$	isoregion isosubregion

Note: Parameters and symbols refer to the model in (2) and (3) in section 4 of the main text.

Table D3. Estimated marginal effects over second category of disaster probabilities and distribution parameters

Variable	$P(y_{it} > 0)$ MEAN	SD	Q2.5%	Q50%	Q97.5%	λ_{it} MEAN	SD	π_{it} MEAN	SD
Country level									
temperature deviation	0.000	0.004	-0.008	0.000	0.008	0.000	0.015	-	-
precipitation deviation	0.043	0.003	0.036	0.043	0.049	0.124	0.015	-0.040	0.013
GDP p.c. growth	0.004	0.004	-0.004	0.003	0.011	0.013	0.013	-	-
population density growth	0.004	0.007	-0.010	0.004	0.018	0.014	0.024	-	-
Global									
trend	0.113	0.031	0.046	0.113	0.172	0.304	0.117	-0.135	0.031
$trend^2$	-0.031	0.030	-0.090	-0.031	0.030	-0.108	0.105	-	-
Δlog(CO2)	0.008	0.005	0.000	0.008	0.016	0.005	0.016	-0.033	0.012

Note: See note in Table A1.

Table D4. Estimated parameters for cointegration analysis

Parameter	Mean	SD	Q2.5%	Q50%	Q97.5%
Regression (7)					
k_1	-5.106	1.728	-2.466	-4.866	-9.531
β_1	0.887	0.299	1.649	0.846	0.431
R^2	0.893	0.031	0.945	0.896	0.824
Regression (8)					
k_2	-1.773	0.857	-0.487	-1.654	-3.782
α_2	-0.365	0.137	-0.123	-0.356	-0.648
β_2	0.309	0.149	0.659	0.288	0.086
Regression (9)					
k_3	-0.049	0.029	0.014	-0.050	-0.104
α_3	0.003	0.007	0.019	0.003	-0.008

β_3	0.009	0.005	0.019	0.009	-0.002

Note: See Table A1.

Appendix E Results displayed in Figure 1 and Figure 3

This Appendix documents estimates and projections of disaster probabilities by country as displayed in Figure 1 and Figure 3 in the main text.

Table E1 (part 1 of 5). Probability of at least on disaster to happen estimated for years 1990 and 2010 and projected to 2040 for the four top tier SSPs

Country	1990	2010	2040			
			SSP1_26	SSP2_45	SSP3_70	SSP5_85
Afghanistan		0.992	1	1	1	1
Albania	0.118	0.562	0.578	0.625	0.673	0.691
Algeria	0.503	0.79	0.876	0.918	0.951	0.96
Andorra	0.302	0.773	0.777	0.817	0.854	0.867
Angola	0.01	0.049	0.297	0.344	0.392	0.409
Antigua and Barbuda	0.254	0.593	0.635	0.681	0.727	0.744
Argentina	0.71	0.857	0.939	0.955	0.968	0.972
Armenia		0.033	0.27	0.318	0.365	0.383
Australia	0.442	0.731	0.793	0.827	0.858	0.868
Austria	0.061	0.145	0.397	0.444	0.492	0.509
Azerbaijan		0.329	0.517	0.564	0.612	0.629
Bahamas	0.024	0.067	0.352	0.399	0.447	0.464
Bahrain	0.168	0.334	0.546	0.593	0.64	0.657
Bangladesh	0.562	0.618	0.788	0.824	0.857	0.868
Barbados		0.523	0.532	0.579	0.626	0.643
Belarus		0.174	0.376	0.424	0.471	0.489
Belgium		0.056	0.272	0.319	0.367	0.384
Belize	0.159	0.231	0.455	0.502	0.55	0.567
Benin	0.205	0.509	0.616	0.663	0.711	0.729
Bermuda	0.011	0.037	0.351	0.398	0.446	0.463
Bhutan	0.682	0.871	0.936	0.954	0.968	0.972
Bolivarian Republic of Venezuela	0.166	0.312	0.487	0.534	0.582	0.599
Bosnia and Herzegovina		0.378	0.496	0.543	0.59	0.607
Botswana	0.447	0.809	0.859	0.889	0.915	0.923
Brazil	0.228	0.397	0.603	0.65	0.695	0.712
Brunei Darussalam	0.026	0.943	0.728	0.773	0.815	0.83
Bulgaria	0.225	0.654	0.726	0.77	0.811	0.826
Burkina Faso	0.021	0.116	0.367	0.415	0.462	0.48
Cambodia		0.412	0.735	0.782	0.829	0.845
Cameroon	0.116	0.512	0.563	0.61	0.658	0.675
Canada	0.446	0.713	0.82	0.866	0.908	0.921
Cape Verde	0.016	0.083	0.331	0.378	0.426	0.444
Central African Republic	0.127	0.474	0.554	0.602	0.65	0.667
Chad	0.126	0.515	0.578	0.626	0.674	0.691
Chile	0.411	0.63	0.786	0.833	0.878	0.893
China	0.864	1	0.999	1	1	1
Colombia	0.804	0.985	1	1	1	1
Comoros	0.042	0.067	0.349	0.397	0.444	0.462
Congo	0.09	0.32	0.47	0.518	0.566	0.583

Table E1 (part 2 of 5)

Country	1990	2010	2040			
			SSP1_26	SSP2_45	SSP3_70	SSP5_85
Costa Rica	0.377	0.772	0.71	0.757	0.804	0.822
Cote d'Ivoire	0.038	0.481	0.499	0.546	0.594	0.612
Croatia		0.506	0.592	0.639	0.687	0.705
Cuba	0.301	0.577	0.69	0.737	0.785	0.802
Cyprus	0.006	0.034	0.315	0.362	0.41	0.427
Czech Republic		0.517	0.627	0.674	0.722	0.739
Denmark	0.011	0.027	0.329	0.376	0.424	0.442
Djibouti		0.192	0.376	0.424	0.471	0.489
Dominica	0.008	0.047	0.315	0.362	0.41	0.427
Dominican Republic	0.306	0.705	0.704	0.752	0.799	0.817
Ecuador	0.401	0.707	0.844	0.889	0.928	0.94
Egypt	0.281	0.489	0.647	0.692	0.736	0.752
El Salvador	0.25	0.665	0.603	0.651	0.699	0.716
Equatorial Guinea	0.009	0.052	0.307	0.355	0.403	0.42
Eritrea		0.162	0.369	0.416	0.464	0.482
Estonia		0.04	0.264	0.311	0.359	0.377
Ethiopia	0.352	0.875	0.93	0.962	0.982	0.987
Federated States of Micronesia		0.028	0.292	0.339	0.387	0.405
Fiji	0.105	0.331	0.509	0.557	0.604	0.622
Finland	0.017	0.051	0.342	0.39	0.437	0.455
France	0.523	0.828	0.923	0.956	0.978	0.983
Gabon	0.033	0.118	0.365	0.413	0.46	0.478
Gambia	0.037	0.423	0.473	0.521	0.569	0.586
Georgia	0.063	0.445	0.531	0.579	0.627	0.644
Germany	0.217	0.466	0.595	0.643	0.69	0.708
Ghana	0.07	0.584	0.581	0.628	0.676	0.694
Greece	0.174	0.629	0.67	0.717	0.765	0.782
Greenland	0.016	0.039	0.337	0.384	0.432	0.45
Grenada	0.018	0.051	0.314	0.361	0.409	0.427
Guam		0.019	0.259	0.307	0.355	0.372
Guatemala	0.454	0.825	0.763	0.81	0.856	0.873
Guinea	0.077	0.286	0.569	0.617	0.665	0.682
Guinea-Bissau	0.01	0.163	0.396	0.444	0.492	0.509
Guyana	0.138	0.236	0.455	0.503	0.55	0.568
Haiti		0.904	0.99	0.997	0.999	0.999
Honduras	0.533	0.743	0.774	0.821	0.867	0.883
Hong Kong	0.165	0.487	0.689	0.736	0.784	0.801
Hungary		0.622	0.677	0.724	0.771	0.789
Iceland	0.073	0.122	0.408	0.455	0.503	0.521
India	0.986	1	1	1	1	1

Table E1 (part 3 of 5)

country_name	1990	2010	2040			
			SSP1_26	SSP2_45	SSP3_70	SSP5_85
Indonesia	0.889	1	1	1	1	1
Iraq	0.044	0.324	0.465	0.513	0.56	0.578
Ireland	0.075	0.112	0.405	0.452	0.5	0.518
Islamic Republic of Iran	0.661	0.899	0.983	0.994	0.998	0.999
Isle of Man	0.289	0.636	0.803	0.849	0.892	0.907
Israel	0.052	0.125	0.394	0.442	0.489	0.507
Italy	0.499	0.874	0.894	0.933	0.963	0.971
Jamaica	0.086	0.412	0.473	0.52	0.568	0.586
Japan	0.637	0.87	0.91	0.946	0.971	0.978
Jordan	0.043	0.109	0.368	0.416	0.464	0.481
Kazakhstan		0.404	0.595	0.643	0.691	0.708
Kenya	0.323	0.884	0.795	0.842	0.886	0.901
Kiribati	0.022	0.085	0.353	0.4	0.448	0.466
Kuwait		0.064	0.295	0.342	0.39	0.408
Kyrgyzstan	0.168	0.414	0.577	0.624	0.672	0.689
Lao People's Democratic Republic	0.349	0.477	0.695	0.743	0.79	0.808
Latvia		0.04	0.263	0.31	0.358	0.376
Lebanon	0.012	0.058	0.304	0.352	0.399	0.417
Lesotho	0.062	0.17	0.417	0.465	0.512	0.53
Liberia	0.017	0.24	0.429	0.476	0.524	0.541
Libyan Arab Jamahiriya		0.076	0.283	0.331	0.378	0.396
Lithuania		0.115	0.32	0.368	0.415	0.433
Luxembourg		0.058	0.274	0.322	0.369	0.387
Macao	0.007	0.056	0.308	0.356	0.404	0.421
Madagascar	0.018	0.212	0.444	0.491	0.539	0.557
Malawi	0.129	0.706	0.724	0.771	0.818	0.835
Malaysia	0.254	0.879	0.835	0.88	0.92	0.933
Maldives		0.139	0.335	0.382	0.43	0.448
Mali	0.09	0.663	0.623	0.67	0.718	0.736
Malta	0.017	0.046	0.334	0.382	0.43	0.447
Marshall Islands		0.088	0.314	0.361	0.409	0.427
Mauritania	0.128	0.501	0.569	0.616	0.664	0.682
Mauritius	0.005	0.065	0.336	0.384	0.431	0.449
Mexico	0.699	0.918	0.985	0.995	0.998	0.999
Mongolia	0.1	0.187	0.419	0.466	0.514	0.532
Montenegro		0.324	0.418	0.465	0.513	0.531
Morocco	0.322	0.6	0.7	0.747	0.795	0.812
Mozambique	0.12	0.654	0.751	0.798	0.845	0.861
Myanmar	0.544	0.825	0.867	0.898	0.925	0.933
Namibia	0.08	0.44	0.547	0.594	0.642	0.66

Table E1 (part 4 of 5)

country_name	1990	2010	2040			
			SSP1_26	SSP2_45	SSP3_70	SSP5_85
Nepal	0.734	0.887	0.985	0.994	0.998	0.999
Netherlands	0.054	0.122	0.385	0.432	0.48	0.498
New Zealand	0.453	0.713	0.849	0.893	0.932	0.943
Nicaragua	0.343	0.608	0.635	0.682	0.73	0.748
Niger	0.137	0.654	0.644	0.691	0.739	0.756
Nigeria	0.138	0.913	0.742	0.789	0.836	0.853
Northern Mariana Islands		0.022	0.253	0.301	0.348	0.366
Norway	0.045	0.1	0.375	0.423	0.47	0.488
Oman	0.01	0.035	0.334	0.381	0.429	0.446
Pakistan	0.803	0.97	0.999	1	1	1
Palau		0.005	0.267	0.315	0.363	0.38
Panama	0.451	0.927	0.781	0.828	0.873	0.889
Papua New Guinea	0.405	0.583	0.702	0.75	0.797	0.815
Paraguay	0.29	0.453	0.633	0.68	0.728	0.746
Peru	0.697	0.871	0.994	0.998	1	1
Philippines	0.838	0.987	1	1	1	1
Plurinational State of Bolivia	0.548	0.71	0.867	0.897	0.923	0.931
Poland		0.435	0.556	0.604	0.651	0.669
Portugal	0.155	0.446	0.538	0.586	0.633	0.651
Puerto Rico	0.121	0.362	0.474	0.522	0.569	0.587
Qatar		0.047	0.262	0.309	0.357	0.374
Republic of Korea	0.571	0.753	0.81	0.856	0.899	0.913
Republic of Moldova		0.326	0.483	0.53	0.578	0.596
Romania		0.911	0.98	0.993	0.998	0.998
Russian Federation	0.635	0.945	1	1	1	1
Saint Kitts and Nevis	0.165	0.494	0.539	0.586	0.634	0.651
Saint Lucia	0.029	0.088	0.328	0.375	0.423	0.441
Saint Vincent and The Grenadines	0.054	0.199	0.388	0.436	0.483	0.501
Samoa	0.008	0.182	0.385	0.433	0.48	0.498
San Marino		0.329	0.453	0.5	0.548	0.565
Sao Tome and Principe		0.046	0.277	0.324	0.372	0.39
Saudi Arabia	0.01	0.029	0.33	0.377	0.425	0.443
Senegal	0.062	0.928	0.692	0.739	0.785	0.801
Serbia		0.464	0.585	0.631	0.677	0.694
Seychelles	0.045	0.497	0.593	0.64	0.687	0.704
Sierra Leone	0.014	0.007	0.36	0.407	0.455	0.473
Singapore	0.148	0.46	0.619	0.665	0.711	0.728
Slovakia		0.063	0.276	0.323	0.371	0.389
Slovenia		0.814	0.887	0.914	0.937	0.944
Solomon Islands		0.025	0.263	0.311	0.359	0.376

Table E1 (part 5 of 5)

country_name	1990	2010	2040			
			SSP1_26	SSP2_45	SSP3_70	SSP5_85
South Africa	0.061	0.194	0.427	0.474	0.522	0.54
Spain	0.105	0.352	0.492	0.54	0.587	0.605
Sri Lanka	0.657	0.946	0.965	0.985	0.994	0.996
Sudan	0.442	0.705	0.821	0.857	0.888	0.898
Suriname	0.741	0.876	0.921	0.943	0.96	0.965
Swaziland	0.016	0.049	0.34	0.387	0.435	0.453
Sweden	0.018	0.049	0.341	0.388	0.436	0.453
Switzerland	0.176	0.346	0.537	0.583	0.629	0.645
Tajikistan	0.163	0.354	0.536	0.583	0.629	0.645
Thailand	0.718	0.897	0.958	0.97	0.979	0.982
The Democratic Republic of the Congo	0.161	0.726	0.682	0.729	0.777	0.794
The Former Yugoslav Republic of Macedonia		0.378	0.509	0.556	0.603	0.621
Timor-Leste		0.286	0.476	0.524	0.571	0.589
Togo	0.117	0.821	0.719	0.765	0.809	0.825
Tonga	0.046	0.136	0.358	0.406	0.453	0.471
Trinidad and Tobago	0.044	0.119	0.367	0.414	0.462	0.479
Tunisia	0.057	0.099	0.376	0.423	0.471	0.488
Turkey	0.039	0.158	0.397	0.444	0.492	0.51
Turkmenistan	0.755	0.909	0.977	0.984	0.989	0.991
Tuvalu		0.009	0.268	0.315	0.363	0.381
U.S. Virgin Islands		0.992	0.995	0.997	0.998	0.999
Uganda	0.041	0.162	0.383	0.43	0.478	0.495
Ukraine	0.204	0.767	0.813	0.85	0.884	0.895
United Arab Emirates	0.025	0.067	0.339	0.386	0.434	0.452
United Kingdom	0.052	0.086	0.378	0.426	0.474	0.491
United Republic of Tanzania	0.031	0.119	0.353	0.401	0.448	0.466
United States	0.417	0.628	0.756	0.795	0.831	0.843
Uruguay	0.496	0.651	0.791	0.831	0.867	0.88
Uzbekistan	0.084	0.206	0.422	0.469	0.517	0.534
Vanuatu	0.044	0.129	0.368	0.416	0.463	0.481
Viet Nam	0.302	0.455	0.664	0.709	0.751	0.767
Yemen		0.103	0.326	0.374	0.421	0.439
Zambia	0.39	0.947	0.883	0.915	0.941	0.949
Zimbabwe	0.257	0.756	0.752	0.795	0.834	0.848

Appendix References

Morice CP, Kennedy JJ, Rayner NA, Jones PD (2012) Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 dataset. J Geophys Res 117(D08101). https://doi.org/10.1029/2011JD017187

Schneider U, Becker A, Finger P, Meyer-Christoffer A, Ziese M (2018) GPCC Full Data Monthly Product Version 2018 at 1.0: Monthly Land Surface Precipitation from Rain-Gauges built on GTS-based and Historical Data https://doi.org/10.5676/DWD_GPCC/FD_M_V2018_100

III. Is financial literacy an economic good?[27]

Abstract

Financial literacy (FL) is generally regarded as an economic good which individuals choose whether or not to consume depending on how much of a contribution they expect it to make to the quality of their financial decision-making. This construct has not, however, been tested empirically. In this study we analyze variations in FL on the part of individuals who experience major life-cycle events that show up in the data and that can be assumed to have repercussions on their personal finances. The analysis of a panel made up of approximately 12,000 people indicates that there is a correlation between 13 of the 17 selected life events and financial decisions, but only one of those events (job training) is associated with a change in FL. This evidence casts doubt upon the conceptualization of FL as an economic good and is in line with a series of other studies that, for one reason or another, have questioned the soundness of the current conceptual approach to FL.

Key words: Finance, consumption, consumer education, measurement, evaluation, mathematical analysis, Chile

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1. Introduction

Financial markets are becoming increasingly complex and are becoming accessible to more and more people. Because of this, individuals' ability to optimize their finances is presumed to have a substantive influence on their well-being (see, for example, Hilgert, Hogarth and Beverly, 2003, and Campbell et al., 2011). This is the origin of the concept of "financial literacy" (FL) as a characteristic that has a decisive influence on an individual's ability to optimize his or her financial standing position.

While the different empirical approaches used to measure people's FL have come in for criticism, it can be argued that the levels of FL found in the general population are substantially lower than they should be (Hogarth and Hilgerth, 2002; Miles, 2004; Christelis, Jappelli and Padula, 2005; Lusardi and Mitchell, 2007a and 2007b; Lusardi, Mitchell and Curto, 2010; Landerretche and Martínez, 2011; Van Rooij, Lusardi and Alessie, 2011; Stone and Neumann, 2012, among others). This has consistently been found to be the case in all the countries for which data are available, and FL levels are particularly low among the poorer segments of the population and among women. It has been observed that this FL deficit not only has a detrimental impact on individuals but has also played a harmful role in markets and in recent global financial crises (Gerardi, Goette and Meier, 2010). Many countries have therefore begun to implement programs designed to boost the population's FL levels in the belief that the social benefits of this type of initiative will far outweigh its costs.

Analyses of such program’s impact on financial behavior have not yielded straightforward results, however (see, for example, Lyons et al., 2006; Hathaway and Khatiwada, 2008; Servon and Kaestnert, 2008; Willis, 2009, Mandell and Klein, 2009). A number of authors attribute this to the FL literature's lack of a sound conceptual framework (Mason and Wilson, 2000; Willis, 2008; Remund, 2010, and Huston, 2010).

In order to develop better policies and impact assessments in this area, a fuller understanding of the process of FL accumulation and decumulation (FLAD) is needed. Thus far, only a very few in-depth studies (Delavande, Rohwedder and Willis, 2008, and Agarwal et al., 2009) have focused on how FL levels may change over people's life cycles or over time or how they may be altered by changes in the surrounding environment.

There is no consensus in the literature regarding the conceptualization of FL (Huston, 2010). Mason and Wilson (2000) have looked into the meaning of "financial literacy", while Remund (2010) says that experts and consumer advocates use the term "to describe the knowledge, skills, confidence and motivation necessary to effectively manage money". Clearly, there are a number of different definitions of FL (based on such factors as numeracy, financial behavior, knowledge and others) but very little clarity about the decision-making process and what role FL plays in it.

The approach most commonly taken in the literature is to treat FL as an economic good whose accumulation is optimized on the basis of its expected contribution to an individual's decision-making process. This amounts to an implicit adoption of the model of FL as an "information good" (Bates, 1990), although some authors use a human capital model instead (see, for example, Delavande, Rohwedder and Willis, 2008). In both cases, the underlying idea is that FL is an economic good about which individuals arrive at optimization-based consumption decisions. FLAD patterns will therefore presumably be influenced by the expected benefit and expected cost of FL acquisition. If the expected benefit increases or the cost decreases, a person can be expected to acquire more FL. This is the origin of the idea that it is desirable to educate people about the importance of FL and to reduce the cost and effort involved in acquiring it. Here, this view will be referred to as the "economic model of FL".

Yet, despite the fact that this approach is so widely used, no empirical assessments have been made of how well the fit between the economic model of FL and FLAD patterns is.

The main objective of this study is to arrive at just such an assessment. In the economic model of FL, the occurrence of an event that has long-term financial implications for a given person will raise the expected value of FL, since the incorporation of new information (the event) may make it necessary to take certain financial decisions. If the occurrence is exogenous to FL, then FL will be expected to increase in response to the event. The impact of events having financially significant implications on individuals' FL was estimated using a representative sample of the Chilean population for the period 2004-2009. The sample corresponds to that used in four rounds (2002, 2004, 2006 and 2009) of a panel survey (the Social Protection Survey); a fifth round was conducted in 2012, but the data from that round are not yet available. These longitudinal data include a module on financial knowledge and skills.

The results of this analysis indicate that there is no significant, consistent variation in FL when an event having substantial financial implications occurs. The study therefore concludes that FL does not behave like an economic good.

The following section covers the data, the selected events, the FL indicators and the statistical analyses used in this study. Sections 3 and 4 report the results and present a discussion of the findings.

2. Methodology and data

In the economic model of FL, the benefit of FL is defined as its expected impact on financial decision-making. If the expected trends in people's income and expenditure flows change, and they therefore have a strong reason to re-evaluate their financial situation, then the expected benefit of acquiring FL will rise. If, at the same time, the cost of acquiring FL remains constant, people would be expected to acquire more FL. A comparison of measurements of FL before and after a change in the expected trend of income and expenditure flows ought to reflect a positive effect under these circumstances.

For this study, we used survey data to select a series of observable events that can reasonably be supposed to trigger changes in people's expected income and expenditure flows. These events are of a sort that has far-reaching, multidimensional effects on people's lives and include changes in civil status, health, job training status and household composition. It is unlikely that changes in FL could be the factor that would bring about these transitions, and it is therefore reasonable to assume that they are exogenous to FL. It can also be reasonably assumed that, given the amount of time between one survey and the next (two years), most of the people concerned will have resolved the attendant time constraints and will have avoided paying a higher "price" to acquire FL. Under these assumptions, we should find some extent of a positive correlation between the events in question and people's financial behavior.

The methodology used for this study was based on the regression of an FL indicator with the occurrence of these events while controlling for fixed effects at the individual level and for variables that change over time. Panel data were used for a sample of approximately 14,000 people over a span of seven years. The events were selected beforehand and those that exhibited a correlation with changes in people's financial portfolios were retained. In addition to fixed effects at the individual level, the econometric model incorporated variations in people's incomes as a control variable, and an independent analysis was conducted of each age, sex and education-level subgroup.

Another reason for using the events that were selected for this study is that they are ones that usually involve coordination with government agencies, which facilitates the implementation of public policies dealing with personal finances. This is why it is so important to understand the FL patterns associated with these events, which can also create "teachable moments" (i.e., certain types of health and education learning opportunities) (Hansen, 1998; Syvertzen, Stout and Flanagan, 2009; Demark-Wahnefried and others, 2005; McBride, Emmons and Lipkus, 2003; McBride and Ostroff, 2003, among others) that may also be applied to the field of FL (Willis, 2008; GAO, 2004; Mandell and Klein, 2007 and 2009). During these teachable moments, people are unusually receptive and are actively seeking out information.

2.1 Data

The data used in this study are drawn from the longitudinal Social Protection Survey, which is conducted roughly every two years in order to obtain information about the operation and development of the social protection system in Chile (Bravo et al., 2004). This study uses data from the last three rounds for which results are available (2004, 2006 and 2009). The questionnaire used in the previous round (2002) was substantially different from the one used in the following rounds, so the 2002 questionnaire could not be used to construct comparable measurements of variables such as income and expenditure. A brief quantitative description of the database is given in Table 1.

Table 1. Number of observations per Social Protection Survey round, 2004-2009

	2004				2006				2009			
	Total		Current contributors to the pension system		Total		Current contributors to the pension system		Total		Current contributors to the pension system	
	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%
Men	5 905	48.3	4 346	54.6	5 905	48.3	4 200	55.1	5 905	48.3	4 442	54.5
Women	6 318	51.7	3 611	45.4	6 318	51.7	3 423	44.9	6 318	51.7	3 699	45.4
Age<35	1 663	13.6	1 092	13.7	1 358	11.1	973	12.8	976	8	790	9.7
34<age<55	5 040	41.2	3 737	47	4 786	39.2	3 453	45.3	4 321	35.4	3 351	41.2
54<age	5 522	45.2	3 130	39.3	6 081	49.8	3 198	41.9	6 928	56.7	4 002	49.1
Educ<=12	9 990	81.7	6 122	76.9	9 935	81.3	5 765	75.6	9 951	81.4	6 177	75.9
12<educ	2 235	18.3	1 837	23.1	2 290	18.7	1 859	24.4	2 274	18.6	1 966	24.1
Total	12 223	100	7 959	100	12 223	100	7 624	100	12 223	100	8 143	100

Source: prepared by the authors on the basis of data from the Social Protection Survey.

The first Social Protection Survey round, conducted in June 2002 and January 2003, used a representative nationwide sample of 17,246 persons registered with the country's pension system. The second round (November 2004 - May 2005) included a sample of approximately 3,000 people who were not covered by the pension system. In the third and fourth rounds (2006 and 2009), only people who had been surveyed in one of the previous rounds were covered. The 2006 round included a new module on financial knowledge and non-cognitive skills.

Balancing panel data from the last three rounds yields a sample with a total of 12,223 observations per round, with 5,905 men (48.3%) and 6,318 women (51.7%).

2.2 Selection of events

The events that were selected meet the following criteria: (i) they are presumably associated with a reassessment of people's long-term financial positions; (ii) they are captured by the available data; and (iii) they exhibit a significant correlation with changes in the consumption of financial goods.

A number of such events were selected beforehand. For each of the consecutive rounds (2004-2006 and 2006-2009), each of these events was coded as 1 or 0, depending on whether or not it occurred. The initial list included 17 events:

1. Birth of a child
2. Retirement of a member of the household (other than the interviewee)
3. Marriage
4. Divorce
5. Widowed
6. Award of a professional degree
7. Award of a diploma
8. Completion of a job training or in-service training course
9. Learning a trade
10. Commencement of a person's first permanent job
11. Becoming unemployed
12. Re-employment
13. Retirement
14. Disablement
15. Termination of a period of disablement
16. Deterioration in health status
17. Improvement in health status

Table 2. Distribution of the occurrence of the selected events, by round and category, 2004-2009 (Number of observations)

Event	Round	Total			Men			Women			Young people			Adults			Older adults			Education<13			Educatio >12		
		0	1	n.a.	0	1	n.a.	0	1	n.a.	0	1	n.a.	0	1	n.a.	0	1	n.a.	0	1	n.a.	0	1	n.a.
1	2004-2006	11592	599	32	5581	301	23	6011	298	9	1161	194	2	4550	224	9	5879	181	21	9466	446	21	1995	146	10
	2006-2009	11655	534	34	5620	260	25	6035	274	9	828	145	2	4130	186	4	6697	203	28	9540	386	23	1972	141	10
2	2004-2006	10913	623	687	5289	280	336	5624	343	351	1206	67	84	4494	98	193	5213	458	410	8881	475	577	1910	140	101
	2006-2009	10692	649	882	5235	269	401	5457	380	481	869	48	58	4008	74	238	5815	527	586	8726	508	715	1834	135	154
3	2004-2006	11674	339	210	5639	176	90	6035	163	120	1266	62	29	4588	102	95	5820	175	86	9476	274	183	2066	61	24
	2006-2009	11386	451	386	5496	238	171	5890	213	215	870	57	48	4017	160	143	6499	234	195	9265	356	318	1981	93	49
4	2004-2006	11940	73	210	5784	31	90	6156	42	120	1324	4	29	4646	44	95	5970	25	86	9698	52	183	2106	21	24
	2006-2009	11734	103	386	5691	43	171	6043	60	215	921	6	48	4124	53	143	6689	44	195	9545	76	328	2048	26	49
5	2004-2006	11927	86	210	5784	31	90	6143	55	120	1325	3	29	4674	16	95	5928	67	86	9670	80	183	2121	6	24
	2006-2009	11721	116	386	5702	32	171	1019	84	215	927	0	48	4162	15	143	6632	101	195	9513	108	328	2070	4	49
6	2004-2006	12148	75		5870	35		6278	40		1318	39		4771	14		6059	22		9933	0		2078	73	
	2006-2009	12150	73		5873	32		2677	41		939	36		4308	12		6903	25		9949	0		2051	72	
7	2004-2006	11867	273	83	5732	141	32	6135	132	51	1302	48	7	4637	111	37	5928	114	39	9682	182	69	2050	89	12
	2006-2009	11985	165	73	5775	88	42	6210	77	31	943	21	11	4222	72	26	6820	72	36	9795	104	50	2054	56	13
8	2004-2006	11285	855	83	5373	500	32	5912	355	51	1213	137	7	4350	398	37	5722	320	39	9408	456	69	1751	388	12
	2006-2009	11736	414	73	5640	223	42	6096	191	31	910	54	11	4119	175	26	6707	185	36	9689	210	50	1911	199	13
9	2004-2006	11848	292	83	5747	126	32	6101	166	51	1295	55	7	4617	131	37	5936	106	39	9647	222	69	2071	68	12
	2006-2009	11988	162	73	5782	81	42	6206	81	31	950	14	11	4222	72	26	6816	76	36	9772	127	50	2078	32	13
10	2004-2006	11711	512		5679	226		6032	286		1175	182		4597	188		5939	142		9532	401		2044	107	
	2006-2009	11851	372		5749	156		6102	216		835	140		4202	118		6814	114		9681	268		2020	103	
11	2004-2006	11163	1060		5472	433		5691	627		1200	157		4341	444		5622	459		9024	909		2019	132	
	2006-2009	11251	972		5471	434		5780	538		877	98		3945	375		6429	499		9118	831		2002	121	
12	2004-2006	11645	578		5587	318		6058	260		1278	79		4545	240		5822	259		9440	493		2067	84	
	2006-2009	11658	565		5596	309		6062	256		907	68		4069	251		6682	246		9483	466		2026	97	

13	2004-2006	11854	369		5725	180		6129	189		1357	0		4772	13		5725	356		9588	345		2133	18	
	2006-2009	11506	717		5546	359		5960	358		975	0		4307	13		6224	704		9274	675		2087	36	
14	2004-2006	11591	613	19	5607	287	11	5984	326	8	1337	19	1	4639	138	8	5615	456	10	9363	555	15	2096	52	3
	2006-2009	11615	554	54	5616	261	28	5999	293	26	966	7	2	4176	127	17	6473	420	35	9406	497	46	2072	46	5
15	2004-2006	11805	399	19	5693	201	11	6112	198	8	1343	13	1	4689	88	8	5773	298	10	9555	363	15	2120	28	3
	2006-2009	11588	581	54	5597	280	28	5991	301	26	962	11	2	4202	101	17	6424	469	35	9377	526	46	2071	47	5
16	2004-2006	11993	224	6	5824	80	1	6169	144	5	1351	6		4692	91	2	5950	127	4	9719	209	5	2140	11	
	2006-2009	11989	226	8	5803	100	2	6186	126	6	968	7		4252	65	3	6769	154	5	9737	204	8	2104	19	
17	2004-2006	11982	235	6	5786	118	1	6196	117	5	1323	34		4692	91	2	5969	110	4	9722	206	5	2123	28	
	2006-2009	12039	176	8	5806	97	2	6233	79	6	960	15		4249	68	3	6830	93	5	9788	153	8	2103	20	

Source: prepared by the authors on the basis of data from the Social Protection Survey.

The frequencies of occurrence of each of these events for each consecutive pair of survey rounds and for each category are shown in Table 2. These 17 events can be grouped into six categories: changes in household structure, changes in civil status, changes in level of education, training, changes in occupational status and changes in health status.

The next step is to confirm that these events actually are associated with a change in financial behavior. In order to do so, we measured the correlation between the occurrence of these events and changes in four variables that entail some sort of interaction between the person concerned and the financial system. These variables are: (i) changes in savings rate; (ii) changes in total debt over income; (iii) changes in health insurance; and (iv) changes in the amount of insurance.

The econometric model used to find correlations was a linear fixed-effect model, since this allowed us to make sure that any omitted static variable that did not interact with the dynamic variables would not influence the results. The incidence of homogeneous phenomena caused by a round or time effect is partially captured by the constant:

$$\Delta Y_{it} = \sum_{j=1}^{17} \beta_j \Delta X_{ijt} + \Delta income_{it} + \Delta houshold\_income_{it} + d_{region\,it} + d_{34} + \delta + \Delta\varepsilon_{it} \qquad (1)$$

where Y denotes the variable of interaction with the financial system, X corresponds to the vector of the 17 events and δ to the constant, $i = 1..N$ indicates the individual concerned, d_{34} is a dummy variable that indicates whether the difference is in the 2006-2009 rounds rather than in the 2004-2006 rounds, d_{region} is a dummy that captures temporal heterogeneity by region, $\Delta income$ is the variation in the logarithm of the interviewee's inter-round income, $\Delta houshold\_income$ is the variation in the logarithm of the income of the rest of the household members and t = 1,2 corresponds to the periods 2004-2006 and 2006-2009, respectively. It is assumed that the variables for all the rest of the observables and unobservables are sufficiently fixed to be eliminated from the model or that they change over time in a similar way for all the individuals concerned and are therefore incorporated in the constant. The rest of the assumptions made by Liker, Augustyniak and Duncan (1985) are also used to obtain consistent, unbiased estimators.

The results of these regressions are shown in Table 3. Each of the four variables that capture interaction with the financial system is analyzed separately.

The criterion used to construct the definitive list of events was the existence of a correlation having a significance level of at least 10% between the event and one of the indicators of interaction with the financial market. This exercise allows us to immediately rule out four events: retirement of a household member, divorce, and the two types of changes in employment status.

In order to rule out the presence of multicollinearity, inter-event correlations were examined. All of these correlations were under 0.1 except in a few cases during the second period and, even in those cases, the correlation was barely above that figure.

Table 3. Regressions in first differences, indicators of interaction with financial markets in comparison to the preliminary selection of events, 2006-2009

Activity / Event	Change in amount of insurance	Change in health insurance	Change in savings rate	Change in debt/income ratio
Birth of a child	0.089	0.053**	0.090	2.252*
Retirement of household member	0.044	0.013	0.067	-0.637
Marriage	0.115	0.054*	0.034	2.665***
Divorce	0.358	0.044	0.031	1.847
Widowed	-0.086	-0.041***	0.069	1.170
Award of a professional degree	0.626	0.236**	0.461***	6.645
Award of a diploma	0.170	0.032	0.089	2.740***
Job training	0.413***	0.082***	-0.069	1.361
Learning a trade	0.230*	0.005	-0.067	-0.191
First permanent job	-0.086	-0.011	-0.150***	0.127
Becoming unemployed	-0.092	0.003	0.044	-0.441
Re-employment	-0.009	-0.022	0.279	-7.497
Retirement of interviewee	-0.156**	-0.014	-0.129***	-0.624
Disablement	0.048	-0.037***	0.070	-0.855
Termination of a period of disablement	-0.086	-0.029***	0.055	-0.163
Improvement in health status	0.183	-0.026	-0.157***	4.737
Deterioration in health status	-0.031	-0.060***	-0.168	0.558

Source: prepared by the authors on the basis of data from the Social Protection Survey.

* significant at 10%; ** significant at 5%; *** significant at 1%.

2.3 FL indicators

Two indicators are used to measure people's stock of FL: their basic financial skills (BFS), which is determined on the basis of information drawn from the last two survey rounds, and their knowledge about the pension system (KPS), which is determined on the basis of information from the last three rounds. This second indicator is intended to capture a different dimension of FL and to replicate the exercise conducted on the basis of BFS while extending it to include the 2004 round.

(a) Measurement of basic financial skills (BFS)

The indicator used to measure BFS was calculated for the 2006 and 2009 rounds on the basis of responses to six questions. These questions were grouped into a submodule whose purpose was to measure people's ability to understand or perform basic mathematical and financial calculations. The questions were as follows:

1. If the probability of falling ill is 10%, how many people out of every 1,000 persons will fall ill?
2. If five people have winning lottery tickets and the jackpot is two million pesos, how much money will each person receive?
3. Suppose that you have $100 in a savings account. The account earns interest at a rate of 2% per year. If you keep the money in your account for five years, how much money will you have at the end of those five years? (four ranges of figures given).
4. Let's say that you have $200 in a savings account. The account interest at a rate of 10% per year. How much will you have after two years?
5. Suppose that you have $100 in a savings account. The account earns interest at a rate of 1% per year. The rate of inflation is 2% per year. If you withdraw your money after one year, you will be able to buy something that costs: (i) more than $100; (ii) exactly $100; (iii) less than $100; (iv) don't know or no response.
6. Is the following statement true or false: “Using a given amount of money to buy shares in one company is less risky than using that same amount of money to buy shares in a number of different companies.”?

Each response is compared with the correct response to arrive at binary variables (knows/does not know). A quantitative description of the responses given by the total sample to each question is shown in the upper portion of Table 4. For all the questions in both rounds, men gave a larger number of correct answers than women did. Young people generally had more correct answers for all the questions except for the question about inflation in 2009, where adults scored higher. More educated people scored higher than their less educated counterparts, with the biggest differences (differentials of over 30%) corresponding to the first three questions. As for inter-round differences, the scores on questions 2, 4, 5 and 6 were generally better for the 2006 round, while the scores on questions 1 and 3 were higher for the 2009 round; these differentials were generally less than 5%, however, except in the case of question 5 (on inflation), where the differential amounts to 7%.

Table 4. Basic financial skills: percentage of correct answers, by round and cohort (Percentages)

Question	Round	Total	Men	Women	Age<35	34<age<55	54<age	Educ<=12	Educ>12
Total sample									
1	2006	44.3	49.8	39.4	60.0	46.7	39.0	37.9	73.0
	2009	44.4	50.0	39.0	65.4	48.0	39.2	37.7	76.0
2	2006	40.4	45.0	36.0	48.6	42.1	37.3	35.7	62.0
	2009	38.4	43.1	34.0	51.9	41.8	34.5	33.2	63.6
3	2006	45.7	49.5	42.2	57.9	47.7	41.6	40.6	69.0
	2009	47.1	51.1	43.2	63.5	50.8	42.5	41.5	72.9
4	2006	1.7	2.3	1.1	2.4	1.8	1.5	0.7	6.1
	2009	1.3	2.0	0.6	2.2	1.4	1.0	0.5	4.9
5	2006	25.2	27.5	23.0	27.1	25.3	24.7	22.2	38.4
	2009	17.8	20.0	15.8	17.8	19.5	16.8	15.3	30.3
6	2006	43.6	46.0	41.3	49.7	45.5	40.7	40.2	59.5
	2009	40.4	43.2	37.7	48.3	45.1	36.4	37.1	55.9
Current contributors to the pension system only									
1	2006	51.9	54.6	48.6	62.0	51.9	48.9	45.0	73.3
	2009	52.3	55.9	48.0	67.7	51.8	49.9	45.2	76.7
2	2006	45.9	48.6	42.6	49.6	45.9	44.9	40.7	62.5
	2009	44.5	47.0	41.5	53.4	45.2	42.3	38.9	63.8
3	2006	51.6	53.9	48.9	59.0	51.5	49.6	45.9	69.4
	2009	54.9	56.8	52.6	66.5	55.1	52.6	49.0	74.3
4	2006	2.1	2.6	1.6	1.9	2.1	2.2	0.9	5.9
	2009	1.6	2.3	0.8	2.2	1.7	1.5	0.6	4.9
5	2006	27.5	29.1	25.5	27.3	26.7	28.3	23.8	38.7
	2009	20.2	21.8	18.3	18.4	20.9	19.9	17.2	30.2
6	2006	47.3	48.6	45.6	50.7	47.2	46.3	43.3	60.0
	2009	44.9	46.3	43.2	48.1	47.4	42.2	41.5	55.9

Source: prepared by the authors on the basis of data from the Social Protection Survey.

The same information is given in the lower portion of Table 4 for the subgroup of persons who were paying into the pension system at the time they were interviewed. In general, the differentials between rounds and categories are much the same as they were in the first case, but the scores are higher in all cases with the exception of the scores for more highly educated persons. This is no doubt due to the existence of a correlation between having a higher level of education and the probability that the person is paying into the pension system.

(b) Measurement of knowledge about the pension system (KPS)

The 2004, 2006 and 2009 rounds of the Social Protection Survey included over 30 questions designed to measure people's knowledge about the pension system. This makes it possible to construct a KPS indicator that can be used in conjunction with the BFS indicator.

Because the wording of some of the questions differed from one round to the next, and given the findings of Lusardi, Mitchell and Curto (2012) regarding the ways in which differences in the wording of questions can significantly influence the answers given, we decided to use only those questions which were worded in the same way in all three rounds. This left us with 11 questions:

1. Do you know what percentage of your taxable income is deducted (was deducted or would be deducted) each month for social security tax? [Between 11.1% and 13]
2. Do you know how the pension fund management boards (AFPS) calculate pension benefits? [On the basis of the balance in the individual pension account, retirement age or other factors]
3. Do you know about or have you heard about the Voluntary Retirement Savings (*Ahorro Previsional Voluntario* (APV)) system that has been in place since 2002?
4. Do you know how much you have in your individual pension account?
5. Do you know how much of a commission your AFP charges for managing your funds?
6. Do you know about or have you heard about multi-funds?
7. Do you know how many different types of funds there are? [5]
8. Do you know what type of fund your pension contributions are in?
9. By law, at what age can a man begin to draw his pension? [65]
10. By law, at what age can a woman begin to draw her pension? [60]
11. Do you know what the different types of old-age pensions are? [Scheduled withdrawals, life annuities, fixed-term withdrawals with a deferred life annuity and immediate life annuities with scheduled withdrawals]

The responses to questions 1, 2, 7, 9, 10 and 11 can be checked, whereas the answers to the other questions consist of statements about the person's knowledge. Bravo et al. (2004, 2006 and 2008) report some discrepancies between self-reported knowledge and actual knowledge, but they nonetheless find a close correlation between the two. Chan and Huff (2003) find that responses regarding self-reported knowledge provide supplementary data about the importance that people attribute to the information referred to in the question and about their degree of assurance in that regard. Landerretche and Martínez (2011) suggest that, in order to avoid overestimating the parameters in question, the results for these types of responses should be regarded as the upper limit for accurate results when the time comes to interpret them, with the assumption being that the actual value is lower.

It is very important to note that several of these questions are posed only to people who are paying into the pension system at the time that they were interviewed. The estimates discussed in the following section include this subsample so that the results for BFS and KPS can be compared. As in the case of the BFS indicator, the responses are coded in order to obtain binary variables (correct/incorrect or knows/does not know). The percentages of correct answers in each round in each of the various categories are given in Table 5.

Table 5. Knowledge about the pension system: percentage of correct answers, by round and cohort, 2006-2009 (Percentages)

Question	Round	Total	Men	Women	Age<35	34<age<55	54<age	Educ<=12	Educ>12
1	2004	22.5	24.0	20.8	26.8	22.3	21.3	19.4	33.0
	2006	19.4	20.0	18.6	24.2	19.1	18.2	16.3	29.4
	2009	16.5	17.5	15.3	23.0	16.5	15.2	13.2	27.7
2	2004	10.8	12.0	9.4	10.3	10.8	11.1	8.6	18.1
	2006	11.4	11.9	10.8	10.9	10.8	12.2	9.5	17.6
	2009	13.1	14.4	11.5	14.7	12.3	13.4	10.8	20.4
3	2004	55.8	56.3	55.2	53.3	57.4	54.7	49.0	78.4
	2006	61.8	61.6	62.1	66.0	62.8	59.4	55.2	82.8
	2009	44.3	44.3	43.6	44.8	45.8	42.9	37.3	67.3
4	2004	50.2	53.8	46.0	44.4	51.7	50.5	47.4	59.6
	2006	50.1	53.1	46.3	41.3	52.0	50.6	47.5	58.4
	2009	43.7	46.2	40.6	35.3	45.4	43.9	41.4	51.3
5	2004	3.1	4.0	1.9	2.3	3.2	3.2	2.2	5.8
	2006	4.9	5.7	3.9	4.7	4.7	5.2	3.6	9.0
	2009	5.1	5.8	4.3	5.8	4.9	5.2	3.8	9.3
6	2004	43.6	44.5	42.5	46.9	44.2	41.7	35.4	71.0
	2006	40.9	42.8	38.6	42.3	41.5	39.8	32.7	67.2
	2009	41.5	43.5	39.2	45.1	42.3	40.2	33.1	69.6
7	2004	17.9	18.8	16.9	17.6	18.4	17.5	12.6	36.0
	2006	17.1	18.4	15.5	18.7	17.0	16.7	12.0	33.5
	2009	24.5	26.2	22.4	27.1	24.5	23.9	17.6	46.9
8	2004	29.4	31.2	27.1	31.1	30.2	27.7	21.6	55.3
	2006	30.2	32.6	27.2	31.4	30.5	29.4	22.7	53.8
	2009	35.0	37.6	31.9	39.2	36.0	33.4	26.7	62.3
9	2004	82.9	83.8	81.8	76.6	83.3	84.7	81.5	87.7
	2006	86.1	87.6	84.4	81.1	85.7	88.1	84.5	91.5
	2009	86.8	90.6	80.4	79.3	85.9	89.0	85.6	90.7
10	2004	79.0	77.7	80.6	74.1	78.6	81.1	77.0	85.8
	2006	81.6	81.4	82.4	77.6	81.6	82.8	78.8	90.7
	2009	73.9	73.7	74.1	70.3	73.8	74.8	71.4	82.1
11	2004	1.1	1.3	0.8	0.5	1.2	1.2	0.6	2.9
	2006	9.1	10.4	7.5	4.8	8.0	11.6	6.7	16.8
	2009	0.9	1.1	0.8	0.5	0.7	1.3	0.4	2.6

Source: prepared by the authors on the basis of data from the Social Protection Survey.

Here again, with the exception of the question about the age at which women can retire, men gave a larger percentage of correct answers to all of the questions in all of the rounds than women did. The ranking in terms of age group is not as clear here as it was in the preceding case. Young people seem to know more about the percentage that is deducted from their pay in the form of social security taxes and about how their funds are being invested, but older adults show themselves to be more knowledgeable about retirement ages and the different types of pension systems. Adults in the intermediate age group appear to know the most about how pension funds are calculated and about how much they have in their accounts. Level of education once again appears to be a significant differentiating factor in terms of the results, with the biggest differentials (around or slightly higher than 30%) being in the level of knowledge about the "solidarity insurance contribution” and about the different pension-fund investment options. The members of this group are the ones who know the least about retirement ages.

As far as inter-round differences are concerned, there does not, generally speaking, appear to be any clear-cut trend. People scored the highest on questions 1, 2, 4 and 6 In the 2004 round, the highest on questions 3, 10 and 11 in the 2006 round, and the highest on questions 5, 8 and 9 in the 2009 round. The differentials between consecutive rounds are below 5%, however, except for a 20% drop between the 2006 and 2009 rounds for the question regarding knowledge about the Voluntary Retirement Savings system. These coefficients were obtained after the panel was balanced, so the same people were the respondents in all of the rounds.

(c) Principal Component Analysis of RIDIT Scores (PRIDIT) indices

In order to obtain the BFS and KPS indicators, interviewee’s responses in each round were recoded using a psychometric methodology for analyzing the principal score components (Lieberthal, 2008). A brief discussion concerning the PRIDIT methodology can be found in annex 1. This is a non-parametric technique that has also been used by Lusardi, Mitchell and Curto (2012) in a similar context to reduce the restrictions associated with some of the assumptions that are implicit in the simple average. In particular, it makes it possible to give more weight to unusual responses in the final indicator (the RIDIT component) and to the responses to questions that appear to explain the responses given to other questions.

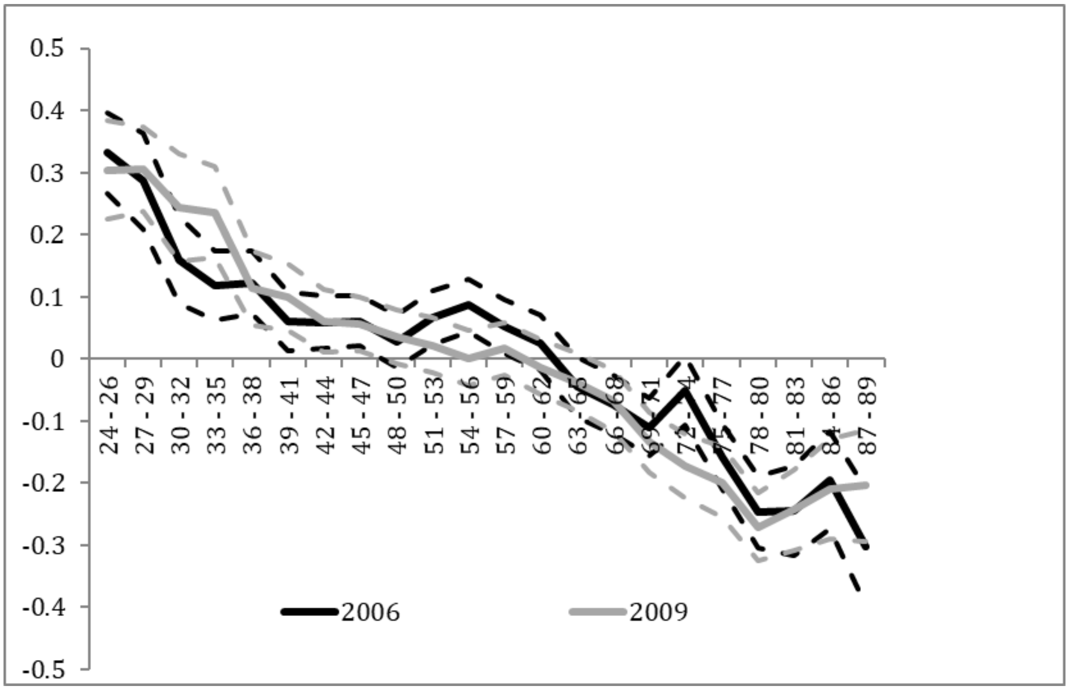
Table 6 provides a quantitative description of these indicators. It should be noted that the indicators constructed using this technique may take on negative values and that the values obtained are comparable only within their particular context (the BFS and KPS indicators cannot be compared to one another). In order to provide a point of reference, the last two columns of Table 6 show the overall average for each Indicator for all the rounds and the corresponding standard deviation.

Table 6. Indicators of financial literacy: averages, by round and category, 2006-2009

Indicator	**bfs**		**bfs (contributors only)**		**kps**		
Round	2006	2009	2006	2009	2004	2006	2009
Total	0.0166	-0.0189	0.1406	0.1138	0,0918	0,1039	0,0324
Men	0.0978	0.0710	0.1857	0.1648	0,1223	0,1410	0,0792
Women	-0.0634	-0.1050	0.0840	0.0521	0,0543	0,0571	-0,0237
Age<=34	0.2332	0.2659	0.2611	0.3015	0,0871	0,1029	0,0704
34<age<55	0.0676	0.0617	0.1417	0.1319	0,0543	0,0571	-0,0237
Age>54	-0.0716	-0.1087	0.1025	0.0634	0,0767	0,0921	0,0109
Edu<=12	-0.1007	-0.1296	0.0105	-0.0038	-0,0741	-0,0590	-0,1293
Educ>12	0.4562	0.4426	0.4967	0.4733	0,5706	0,5496	0,5270
Mean	0.0000		0.1277		0.0777		
Standard deviation	0.7052		0.6936		0.7513		

Source: prepared by the authors on the basis of data from the Social Protection Survey.
BFS: Basic financial skills.
KPS: Knowledge about the pension system.

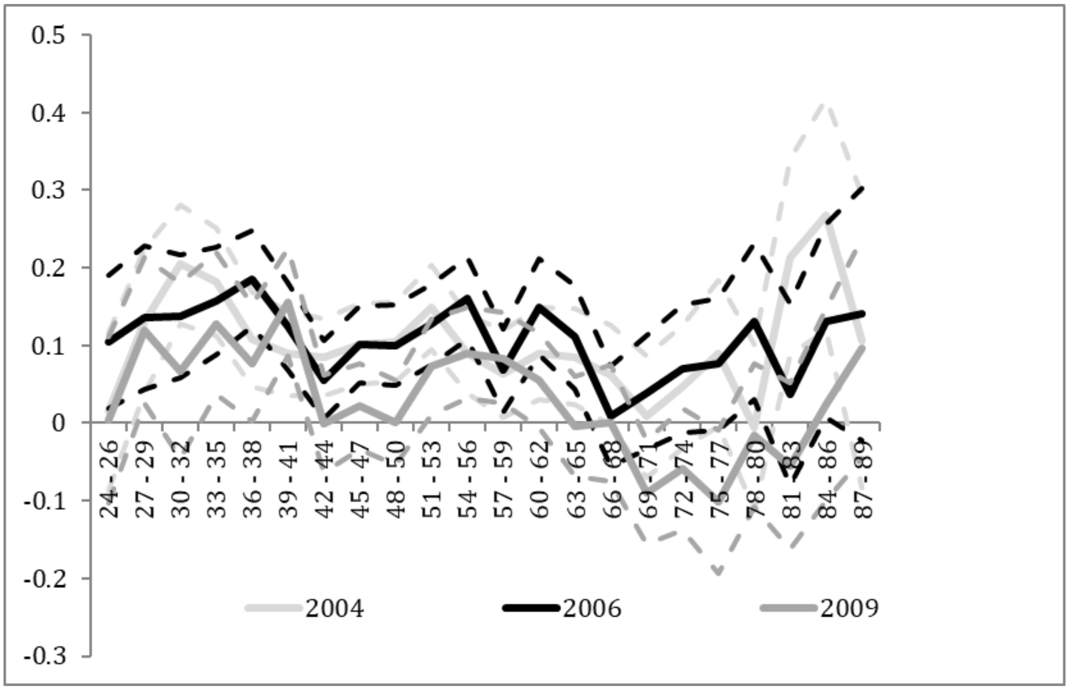
Figure 1. Average values for the BFS indicator, by age group, for each round (Confidence intervals of 10%)



Source: prepared by the authors on the basis of data from the Social Protection Survey.
BFS: Basic financial skills.
Note: The dotted lines indicate the confidence intervals.

As can be seen from the analysis of the responses to the survey questions, men tended to exhibit a greater extent of FL than women did. This finding is corroborated by all of the indicators, with differentials of between approximately 0.10 and 0.25 standard deviations. The value of the BFS indicator appears to decline as people age, whereas the values of the KPS indicator do not exhibit any clear-cut trend (see Figure 1 and 2).

Figure 2. Average values for the KPS indicator, by age group, for each round (Confidence intervals of 10%)



Source: prepared by the authors on the basis of data from the Social Protection Survey.
KPS: Knowledge about the pension system.
Note: The dotted lines indicate the confidence intervals.

2.4 Statistical analysis

The statistical analysis focused on comparisons of the results for a given respondent as measured by the two FL indicators in consecutive rounds. The dependent variable is the change in the FL indicator and the independent variables are the occurrence or non-occurrence of the selected events. The 13 types of events are all included at once at the same time in the same regression.

Here too, a linear fixed-effect regression was used:

$$\Delta Y_{it} = \sum_{j=1}^{13} \beta_j \Delta X_{ijt} + \Delta income_{it} + \Delta houshold\_income_{it} + d_{region\,it} + d_{34} + \delta + \Delta\varepsilon_{it} \quad (2)$$

where Y corresponds to the knowledge indicator, X to the vector for the 13 teachable moments, δ to the constant that captures the linear time effect; $\Delta income$ and $\Delta houshold\_income$ are the differentials in the logarithms for the income of the interviewee and for the rest of the household, respectively; d_{region} is a dichotomous variable, by region; d_{34} indicates whether the observation is for the period between 2006 and 2009; , $i = 1..N$ denotes the individual In question; and $t = 1, 2$ corresponds to 2006 or 2009, respectively. It is assumed that the variables for all the rest of the observables and unobservables are sufficiently fixed to be eliminated from the model. The other assumptions are the same as they were for the preceding regressions.

3. Results

An analysis of the sample as a whole yields results (shown in the first column of Table 7) that generally hold true for the subsamples (see the remaining columns in Table 7) as well: only 1 of the 13 events that were selected is clearly associated with variations in the FL indicator. This event –job training– has a significant impact on both basic financial skills (BFS) and knowledge about the pension system (KPS), with coefficients of 0.271 and 0.630 for the PRIDIT indicators of BFS and KPS, respectively. This is far higher than the median for these indicators (around 0.10 in both cases). None of the other 12 events had a significant impact.

In the subsamples, the only education-related event that had an impact on FL was job training.

An analysis of the subsamples by sex, age and education yields some additional results but does not reflect any pattern that could be extrapolated to the overall sample. The most salient of these results have to do with the impact of changes in health status among women and among people below 54 years of age. In these subsamples, health-related events have a positive influence on BFS but a negative one on KPS. The possible explanations for this may include the presence of divergent patterns in the appreciation and depreciation of individuals' FL stocks or to movements into and out of the labour force.

In this study, all the regressions have been replicated using indicators calculated as simple averages rather than using principal components analysis of RIDIT scores ((PRIDIT). The two exercises yielded similar results.

Table 7. Results of the regressions

	Total sample	Men	Women	Age<35	34<age<55	Age>54	Educ<13	Educ>12
Event	**bfs indicator - total sample**							
Birth of a child	0.154***	0.09	0.199***	0.066	0.057	0.267***	0.161**	0.018
Marriage	0.053	0.086	0.013	-0.019	0.066	0.055	0.04	0.054
Widowed	-0.187	-0.461	-0.069	0.820***	-0.427	-0.149	-0.12	-0.13
Professional degree	0.18	0.045	0.274*	0.350**	-0.22	-0.003	-	-0.231*
Diploma	0.129*	0.055	0.162	-0.277	0.116	0.368**	0.195**	-0.255**
Job training	0.363***	0.334***	0.360***	0.290**	0.288***	0.470***	0.297***	0.081
Learning a trade	0.034	0.211*	-0.131	0.075	-0.032	0.13	0.024	-0.093
First permanent job	-0.06	-0.03	-0.052	-0.096	-0.096	-0.083	-0.033	0.03
Retirement	-0.287***	-0.299	-0.253***	-	-0.704***	-0.200***	-0.222***	-0.039
Disablement	-0.148**	0.008***	-0.255***	0.059	-0.032	-0.174**	-0.145**	0.128
Disablement ending	-0.056	-0.03	-0.079	0.902***	0.037	-0.068	0.002	-0.109
Health improvement	0.105	-0.331**	0.426***	0.560***	0.303**	-0.125	0.181	0.450*
Health deterioration	0.029	-0.032	0.042	0.024	-0.016	0.044	0.065	-0.11
Event	**bfs indicator - persons paying into the pension system only**							
Birth of a child	0.104*	0.052	0.139*	0.075	0.013	0.198**	0.114*	0.01
Marriage	0.027	0.012	0.045	-0.14	0.099	0.009	0.005	0.027
Widowed	-0.389	-0.116	-0.493	0.758***	-0.918***	-0.509**	-0.392	-0.256
Professional degree	0.196*	0	0.325***	0.358**	-0.334**	0.177	-	-0.166
Diploma	0.059	0.019	0.083	-0.411***	0.11	0.241	0.129	-0.273**
Job training	0.271***	0.263***	0.274***	0.212*	0.228***	0.338***	0.212***	0.055
Learning a trade	-0.034	0.252**	-0.248**	-0.001	-0.141	0.138	-0.02	-0.121
First permanent job	-0.066	-0.038	-0.067	-0.193	-0.063	-0.032	-0.073	0.101
Retirement	-0.280**	-0.431***	0.163	-	-0.942***	-0.189*	-0.195*	-0.25
Disablement	0.039	0.091	0.003	-0.031	0.12	-0.011	0.028	0.115
Disablement ending	0.196**	0.188	0.225	0.776***	0.205*	0.156	0.217**	0.241
Health improvement	0.057	-0.361**	0.325*	0.517***	0.348**	-0.305	0.142	0.432*
Health deterioration	0.045	-0.089	0.163	0.091	0.008	0.041	0.051	0.02
Event	**kps indicator**							
Birth of a child	0.087	0.039	0.125	-0.026	0.058	0.249**	0.105	-0.02
Marriage	0.124	0.116	0.105	0.207	-0.048	0.207	0.122	0.06
Widowed	-0.489	-0.227	-0.613**	0.988***	-0.735***	-0.635*	-0.453	-0.594***
Professional degree	-0.004	0.105	-0.062	-0.212	-0.166	0.256	-	-0.444***
Diploma	0.392***	0.546***	0.259**	0.315*	0.336***	0.585***	0.341***	0.184**
Job training	0.630***	0.646***	0.623***	0.709***	0.624***	0.607***	0.609***	0.301***
Learning a trade	0.241***	0.289**	0.188	0.001	0.161	0.468***	0.249***	0.138
First permanent job	-0.214**	-0.015	-0.325***	-0.141	-0.391***	-0.016	-0.226***	-0.023
Retirement	-0.209	-0.21	-0.155	-	-0.743***	-0.155	-0.071	-0.436
Disablement	-0.211**	-0.147	-0.308**	-0.108	0.013	-0.431***	-0.224***	-0.108
Disablement ending	-0.148	-0.13	-0.183	0	-0.239*	-0.089	-0.132	0.042
Health improvement	-0.343***	-0.407**	-0.285*	-0.861***	-0.349**	-0.282	-0.206**	-0.348
Health deterioration	0.099	-0.067	0.232	0.537***	0.168	-0.114	0.118	0.098

Source: prepared by the authors on the basis of data from the Social Protection Survey.

BFS: Basic financial skills.

KPS: Knowledge about the pension system.

* significant at 10%; ** significant at 5%; *** significant at 1%.

4. Discussion

Given the importance that is generally ascribed to financial literacy (FL) in terms of its implications for people's well-being, and in view of a number of studies that indicate that the population's level of FL is quite low, various government programmes designed to increase the population's level of FL have been introduced. There is, however, no consensus in the literature as to the effectiveness of these programmes or about the robustness of the current conceptual approach to FL.

According to the most prevalent way of thinking about FL (referred to here as the "economic model of FL"), people decide how much FL to acquire based on the expected benefits that it will yield in terms of decision-making. In this study, however, the economic model of FL did not fit the data very well, since the analysis did not turn up conclusive evidence of an increase in people's FL when they experienced events that are associated with changes in financial status. This conclusion was reached by analysing two different indicators of FL, both in conjunction with one another and separately, on the basis of a panel of over 12,000 respondents who were surveyed up to four times within seven years. This sample was also divided up into several subsamples.

In short, it is not clear that the economic model is a good fit for FL. While some criticism might be aimed at this study in terms of the quality of the data or of the FL indicators or the validity of the empirical strategy that it has employed, the fact remains that it backs up a number of other studies that have, for one reason or another, cast doubt upon the soundness of the current construct of FL.

It is possible that FL CANNOT be reduced to a simple concept. Even in a more general context, information goods are quite complex (Bates, 1990; Rafaeli and Raban, 2003). It may also be that FL should be viewed as an individual trait which, like intelligence, does not change in the short run. A model of fluid intelligence versus crystalized intelligence has been proposed that may help us to come to grips with a possible association between FL and age (Agarwal et al., 2009). Or perhaps FL is more a matter of attitude than of knowledge per se. Yet another possibility, which would not preclude the preceding one, is that individuals update their FL in ways that cause it to appreciate and/or depreciate such that the net variation in FL is usually very small.

References

Agarwal S., Driscoll J., Gabaix X. and Laibson D. 2009. The age of reason: Financial decisions over the life-cycle with implications for regulation. *Brookings papers of economic activities*. 2009. pp. 51-101.

Bates, Benjamin J. 1990. Information as an economic good: A re-evaluation of theoretical approaches. In B. D. Ruben & L. A. Lievrouw (Eds.), *Mediation, Information, and Communication. Information and Behavior*. Volume 3 (pp. 379-394).

Bravo D., Behrman J.R., Mitchell O. S. and Todd P. E. 2004. Análisis y Principales Resultados, Primera Encuesta de Protección Social. Historia Laboral y Seguridad Social.

Bravo D., Vasquez J., BehrmanJ. R., Mitchell O. S. and Todd P. E. 2006. Encuesta de Protección Social 2004: Presentación General y Principales Resultados.

Bravo D., Eguiguren J.M., Rau T. and Vasquez J. 2008. Determinantes del Ahorro Previsional Voluntario en Chile. *Centro de Microdatos, Departamento de Economía, Universidad de Chile*.

Brockett P. L., Derrig R. A., Golden L. L., Levine A. and Alpert M. 2002. Fraud classification using principal component analysis of RIDITs. *The Journal of Risk and Insurance*. 69 (3), pp. 341-371.

Chan, Sewin and Huff S., Ann. 2003. What you don't know can't help you: Pension knowledge and retirement decision making. *NBER WP* 10185.

Campbell J. Y., Jackson H. E., Madrian, B. C. and Tufano, P. 2011. Consumer financial protection. *Journal of Economic Perspectives*. 25 (1), pp. 91-114.

Christelis D., Jappelli T. and Padula M. 2005. Health risk, financial information and social interactions: The portfolio choice by European elderly households. *Working paper, University of Salerno*.

Delavande, A., Rohwedder, S. and Willis, R. 2008. Preparation for retirement, financial literacy and cognitive resources. *University of Michigan Retirement Center Research, Working Paper, WP* 2008-190.

Demark-Wahnefried W., Aziz N. M., Rowland J. H. and Pinto B. M. 2005. Riding the crest of the teachable moment: Promoting long-term health after the diagnosis of cancer. *Journal of Clinical Oncology*. 23 (24), pp. 5814-5830.

Fajnzylber, E, Plaza, G. and Reyes, G. 2009. Better-informed workers and retirement savings decisions: Impact evaluation of a personalized pension projection in Chile. *Superintendencia de Pensiones de Chile, documento de Trabajo* Nº31,

GAO. Government Accountability Office. 2004. The federal government's role in improving financial literacy. Highlights of a GAO forum, GAO-05-93SP.

Gerardi, K. and Goette, L. 2010. Financial literacy and subprime mortgage delinquency: Evidence from a survey matched to administrative data. *Federal Reserve Bank of Atlanta. Working Paper Series* No. 2010-10.

Hansen, E. J. 1998. Creating teachable moments… and making them last. *Innovative Higher Education*. 23(1). pp. 07-26

Hastings, J., Tejeda-Ashton, L. 2008. Financial literacy, information, and demand elasticity: Survey and experimental evidence from Mexico. *NBER Working Paper* No. 14538.

Hathaway I. and Khatiwada S. 2008. Do financial education programs work? *FRB of Cleveland. Working Pape*r No. 08-03.

Hilgert, M. A., Hogarth, J. M., and Beverly, S. G. 2003. Household financial management: The connection between knowledge and behavior. *Federal Reserve Bulletin*. 89(7). 309-322.

Hogarth, J. and Hilgert, M. 2002. Financial knowledge, experience and learning preferences: Preliminary results from a new survey on financial literacy. *Consumer Interest Annual*, 48.

Huston, S. J. 2010. Measuring financial literacy. *Journal of Consumer Affairs, Special Issue: Financial Literacy*. 44(2). pages 296–316.

Landerretche, O. and Martínez, C. 2011. Voluntary savings, financial behavior and pension finance literacy: Evidence from Chile. *Serie Documentos de Trabajo, Departamento de Economía, Universidad de Chile*, SDT 328.

Lieberthal R.D. 2008. Hospital Quality: A PRIDIT approach health services research. *June*. 43(3): 988–1005.

Liker, J. K., Augustyniak, S. and Duncan, GJ. 1985. Panel Data and Models of Change: A Comparison of First Difference and Conventional Two Wave Models. *Social Science Research*. 14. pp. 80-101.

Lusardi, A. and Mitchell, O. 2006. Financial literacy and planning: implications for retirement and wellbeing. *DNB Working paper* 078.

Lusardi A. and Mitchell O. 2007a. Baby boomer retirement security: The role of planning, financial literacy, and housing wealth. *Journal of Monetary Economics*. 54. pp. 205-224.

Lusardi A. and Mitchell O. 2007b. Financial literacy and retirement preparedness: Evidence and implications for financial education. *Business Economics*. pp. 35-44.

Lusardi, A. 2008. Financial literacy: An essential tool for informed consumer choice?. *Center for Financial Studies* WP No. 19.

Lusardi A., Mitchell O. and Curto V. 2010. Financial literacy among the young. *Journal of Consumer Affairs. Special Issue on Financial Literacy*. 44. pp. 358-380.

Lusardi A., Mitchell, O. and Curto V. 2012. Financial sophistication in the older population. Pension Research Council, University of Pennsylvania. *NBER Working Paper* No. 17863.

Lyons, A. C., Palmer, L., Jayaratne, K. S. U. and Scherpf, E. 2006. Are we making the grade? A national overview of financial education and program evaluation. *Journal of Consumer Affairs*. 40(2). pp 208–235.

Mason, C. and Wilson, R. 2000. Conceptualizing financial literacy. *Business School, Laughborough University, Research Series Paper* 2000:7.

Mandell, L. and Klein, L.S. 2007. Motivation and financial literacy. *Financial Services Review*. 16(2). pp. 105-116.

Mandell, L. and Klein, L.S. 2009. The impact of financial literacy education on subsequent financial behavior. *Journal of Financial Counseling and Planning*. 20(1). pp. 16.

McBride, C.M., Emmons, K.M. and Lipkus, I.M. 2003a. Understanding the potential of teachable moments: The case of smoking cessation. *Health Education Research*. 18(2). pp. 156-170.

McBride, C.M. and Ostroff, J.S. 2003b. Teachable moments for promoting smoking cessation: the Context of cancer care and survivorship. *Cancer Control*. 10(4). pp. 325–333.

Miles, D. 2004. The UK mortgage market: Taking a longer-term view. *The Stationery Office*.

Remund, D.L. 2010. Financial literacy explicated: The case for a clearer definition in an increasingly complex Economy. *Journal of Consumer Affairs*. 44(2). pp. 276-295.

Servon, L.J. and Kaestnert, R. 2008. Consumer financial literacy and the impact of online banking on the financial behavior of lower-income bank bustomers. *Journal of Consumer Affairs*. 42(2). pp. 271–305.

Sheizaf, R., and Raban. D. 2003. Experimental investigation of the subjective value of information in trading. *Journal of the Association for Information Systems*. 4(5). pp 0.

Stone, L.O. and Neumann, B. 2012. Gender differences in preparedness to meet retirement's challenges. Book chapter. *Key Demographics in Retirement Risk Management*, edited by Leroy Stone, pp. 109-125.

Syvertzen, A.K., Stout, M. D. and Flanagan, C. A. 2009. Using elections as teachable moments: a randomized evaluation of the student voices civic education programs. *American Journal of Education*. 116(1), pp. 33-67.

Van Rooij, M., Lusardi, A. and Alessie, R. 2011. Financial literacy and stock marker participation. *Journal of Financial Economics*. 101(2), pp. 449-472.

Willis, L. E. 2008. Against financial-literacy education. *Iowa Law Review*. 94. pp. 197-285.

Willis, L. E. 2009. Evidence and ideology in assessing the effectiveness of financial literacy education. *San Diego Law Review*. 46. pp. 415-925.

Appendix

PRIDIT (i.e., principal component analysis of RIDIT scores) is a non-parametric aggregation technique that involves using two different procedures to rank samples based on categorical observables (Lieberthal, 2008).

The RIDIT methodology has been developed to analyse categorical (in this case, binary) variables serving as proxies for unobservables (Lieberthal, 2008). The underlying reason for using the RIDIT methodology in this study is that an incorrect response may provide more information about a person's level of FL than a correct one, and vice versa. This is because there are some questions that most people answer correctly and, in these cases, the incorrect answers allow us to identify a particular group of individuals; by the same token, when dealing with questions that most people get wrong, the correct answers provide us with more information.

Assigning ones and zeros to all correct and incorrect answers as a basis for constructing the indicator presupposes, first, that FL is metrically measurable —an assumption that we will not take exception to— and, second, that the metric can be scaled with equal intervals between responses for each survey question (Brockett et al., 2002). RIDIT deals with this problem by using sample information for each question to assign different values or weights to the responses (Lieberthal, 2008).

In line with Brockett et al. (2002), the following algorithm was used to construct the RIDIT scores in this study: is the sample probability of obtaining answer i for question t, where $i = 0, 1$ is the number of categories corresponding to answer t. RIDIT scores are therefore determined as follows:

$$R_{ti} = \sum_{j<i} \hat{p}_{ij} - \sum_{j>i} \hat{p}_{ij}$$

Thus, rather than assigning zeros and ones, we assign R_{t0} and R_{t1} to the answers to each question t. This score rises monotonically in the different categories, with the original classification being maintained at the same time that $E\left(R_t\right) = 0$ is fulfilled. In the words of Brockett et al. (2002), this method "eliminates the necessity of assigning integer values in an ad hoc fashion … and improves the statistical characteristics of the resulting scored data for subsequent standard statistical analysis, whatever it is" (Brockett et al., 2002).

PRIDIT: Once the RIDIT scores for each question have been obtained, the principal component analysis weights the questions on the basis of how important a role they play in terms of the variance of the final scores. A convergent algorithm is used to compute the weightings, with the questions that are the least correlated with a linear combination of the other questions being given a greater weighting, since they are the ones that provide the most information. In other words, greater attention is devoted to the "strangest" answers when the time comes to compute the final scores (Lusardi, Mitchell and Curto, 2012).

Annex: Cover pages of published papers and acceptance mail

A. Fortunato, Herwartz, H., López, R. and Figueroa B. E. 2022 Carbon dioxide atmospheric concentration and hydrometeorological disasters. *Natural Hazards* (2022). DOI: 10.1007/s11069-021-05172-z

Natural Hazards
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ORIGINAL PAPER

Carbon dioxide atmospheric concentration and hydrometeorological disasters

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Abstract

We study the long-run connection between atmospheric carbon dioxide (CO_2) concentration and the probability of hydrometeorological disasters using a panel of 193 countries over the period 1970–2016 providing annual disaster projections to the year 2040 for each of these countries. Generating accurate predictions on where hydrometeorological disasters have greater chances to occur, may facilitate preparedness and adaption to such disasters, thus helping to reduce their high human and economic costs. We estimate the probabilities of hydrometeorological disasters at country levels using Bayesian sampling techniques. We decompose the probability of country disaster into the effects of country-specific factors, such as climatological and socio-demographic factors, and factors associated with world climate, which we denote global probability of disaster (GPOD). Finally, we subject these GPOD time paths to a cointegration analysis with CO_2 concentration and provide projections to the year 2040 of the GPOD conditional on nine Shared Socioeconomic Pathways scenarios. We detect a stable long-term relation between CO_2 accumulation and the GPOD that allows us to determine projections of the latter process conditional on the former. We conclude that readily available statistical data on global atmospheric concentrations of CO_2 can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of hydrometeorological disasters.

Keywords Hydrometeorological hazards · Carbon dioxide · Disaster forecast · Natural disasters

1 Introduction

The United Nations Intergovernmental Panel on Climate Change (IPCC) has concluded that increases in well-mixed greenhouse gas (GHG) concentrations since 1750 are unequivocally caused by human activities and that, as a result of that, it is also unequivocal that human influence has warmed the Earth's atmosphere, ocean and land (IPCC 2014,

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Is financial literacy an economic good?

Rubén Castro and Andrés Fortunato

ABSTRACT

Financial literacy (FL) is generally regarded as an economic good which individuals choose whether or not to consume depending on how much of a contribution they expect it to make to the quality of their financial decision-making. This construct has not, however, been tested empirically. In this study we analyse variations in FL on the part of individuals who experience major life-cycle events that show up in the data and that can be assumed to have repercussions on their personal finances. The analysis of a panel made up of approximately 12,000 people indicates that there is a correlation between 13 of the 17 selected life events and financial decisions, but only one of those events (job training) is associated with a change in FL. This evidence casts doubt upon the conceptualization of FL as an economic good and is in line with a series of other studies that, for one reason or another, have questioned the soundness of the current conceptual approach to FL.

KEY WORDS Finance, consumption, consumer education, measurement, evaluation, mathematical analysis, Chile

JEL CLASSIFICATION A20, D14, G11, I20, J26

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A. **Fortunato** and Herwartz, H. 2022 State Dependence of Fiscal Multipliers in Chile - An Independent Component Approach to Identification. *Latin American Economic Review* (Forthcoming)

B.

[LAER] Editor Decision

Dear Andres Fortunato, Helmut Herwartz:

I am pleased to inform you that your manuscript XXXXXX, titled "State Dependence of Fiscal Multipliers in Chile - An Independent Component Approach to Identification" has been accepted for publication in Latin American Economic Review (LAER).

Before publication, our production team will check the format of your manuscript to ensure that it conforms to the standards of the journal. They will be in touch shortly to request any necessary changes, or to confirm that none are needed.

Articles in this journal may be held for a short period of time prior to publication. If you have any concerns, please contact the journal. Any final comments from our reviewers or editors can be found below.

We look forward to publishing your manuscript and I hope you will consider Latin American Economic Review again in the future.

Best wishes,

Dr. Fausto Hernandez
Editor
Latin American Economic Review (LAER)