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the role of survey-based information

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FORECASTING CORPORATE CAPITAL ACCUMULATION IN ITALY: THE ROLE OF SURVEY-BASED INFORMATION

by Claire Giordano*, Marco Marinucci* and Andrea Silvestrini *

Abstract

While there is a vast macroeconomic literature that singles out the main drivers of capital accumulation in advanced economies during and after the global financial and sovereign debt crises' recessionary phase, there is much less research seeking to identify both models and variables that possess out-of-sample forecasting ability for gross fixed capital formation. Moreover, micro-founded variables are scarcely employed in macroeconomic forecasting of real investment. We fill this gap by considering a battery of univariate and multivariate time-series models to forecast investment of non-financial corporations in Italy, an interesting case study due to its steep downturn during the two afore-mentioned crises. We find that a vector error correction model augmented with firm survey-based variables accounting for business confidence, demand uncertainty and financing constraints generally outperforms the autoregressive benchmark and a series of competing multivariate time-series models in various, alternative, evaluation samples that take into account the impact of both the global financial crisis and the sovereign debt crisis on forecast accuracy.

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1 Introduction

Since the seminal contribution in Hall and Jorgenson (1967), researchers have long sought to pinpoint the main determinants of gross fixed capital formation (GFCF), in order to predict its evolution and, ultimately, GDP growth. The double recessionary phase in the euro area, made up of both the global financial crisis (GFC) in 2008–2009 and the sovereign debt crisis (SDC) in 2011–2013, renewed interest in this topic and led to a number of macroeconomic analyses aimed at singling out the main drivers of capital accumulation, such as Banerjee et al. (2015), Barkbu et al. (2015) and Bańbura et al. (2018).

Several studies (Bontempi et al., 2010; Busetti et al., 2016; Bacchini et al., 2018; Giordano et al., 2019) have focused specifically on Italy, an insightful case-study in that, after growing at a comparable rate to its peer euro-area economies since 1995 (the initial year of official national account data), Italy's GFCF then experienced a significantly more pronounced downturn during the double recession and a more sluggish recovery thereafter. In this country, non-financial corporations (which we loosely also refer to as "firms" in this article) alone undertake about half of total GFCF (Giordano et al., 2016). Italian firms' real investment rate dropped from over 24 per cent at the beginning of 2007 to a trough of about 19 at the end of 2013 (Figure 1); since then, it started to pick up again, but has still not reached the pre-crisis peak. The main conclusion of the afore-mentioned articles has been that, in addition to the standard factors underlying Hall and Jorgenson (1967)'s capital accumulation model, namely real output and the real user cost of capital, other drivers of investment are important, such as business confidence, uncertainty and financial conditions, in particular during crisis episodes.

Figure 1: **Firms' real investment rate and GFCF dynamics**
(percentage values and percentage changes on the previous quarter)
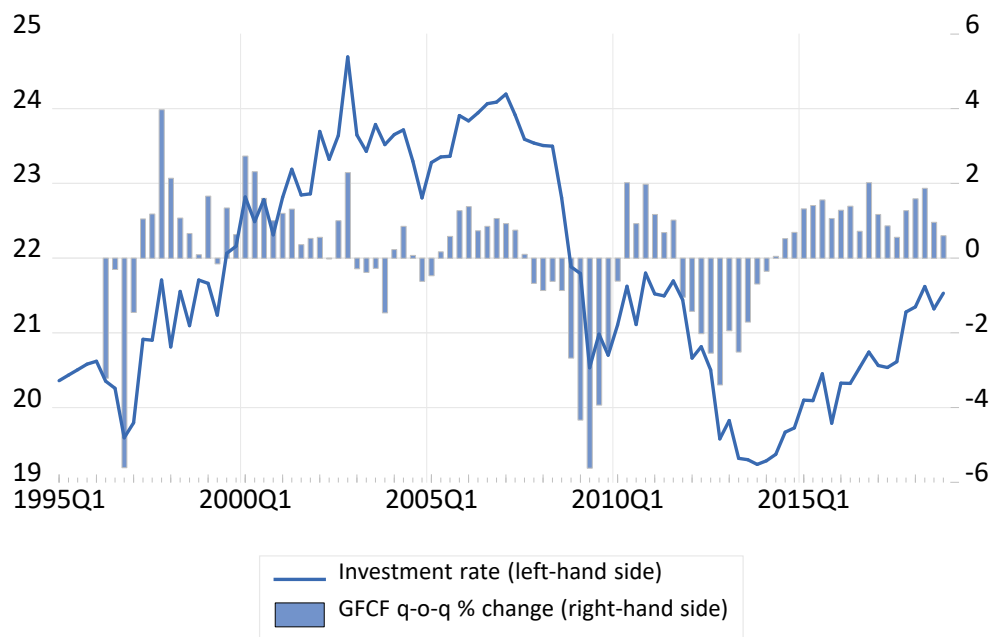
Source: Authors' calculations on Istat data. Notes: The real investment rate is computed as the ratio between non-financial corporations' GFCF and their value added, both appraised at constant prices and seasonally adjusted, multiplied by 100. GFCF is obtained by deflating nominal GFCF with the total non-housing investment deflator.

This article assesses the predictive power of a cointegrated vector error correction model (VECM), as popularised by Engle et al. (1983), Johansen (1988) and Johansen (1995), which takes into account both the standard, long-run drivers of investment dynamics of non-financial corporations in Italy, and also the short-run effect of additional variables, which we construct also using firm survey data. It therefore complements the afore-mentioned studies, which mainly undertake historical assessments of capital accumulation, disregarding the forecasting ability of their proposed models. This study also adds to other forecasting exercises of key macroeconomic variables, such as Paccagnini (2019), which addresses a similar issue of the role of financial factors, yet referred only to the United States during its Great Recession. Finally, by widely exploiting survey-based information, it adopts a micro-macro approach, similarly to D'Aurizio and Iezzi (2011) and Girardi and Ventura (2019) specifically for the Italian case.

In more detail, this article's contribution to the literature is threefold. First, within a VECM framework, and compared to other models, it investigates the gain in forecasting power of corporate investment dynamics in Italy linked to the inclusion of business confidence, demand uncertainty and financial factors. Second, this study exploits firm survey data to construct proxies of the latter variables and, wherever possible, to compare their performance with that of alternative macroeconomic measures. Third, this article evaluates the exceptional nature of firms' investment dynamics during the GFC and the SDC, by considering three alternative in-sample estimation periods, namely the pre-GFC, the pre-SDC and the pre-2013 (i.e., until the end of the SDC) periods.

Results show that our cointegrated VECM specification, which accounts for multivariate feedback between non-financial corporations' real investment, real output, real user cost of capital and a cointegrating relationship among them, integrated by three weakly exogenous variables (uncertainty, business confidence and financial factors), outperforms the autoregressive benchmark and a series of competing multivariate time-series models. This result holds when a credit-constraint variable is employed to measure fi-

nancial factors; moreover, when the in-sample estimation window includes the two crisis episodes, the cointegrated VECM specification with a survey-based uncertainty indicator presents the highest forecasting power. As found more generally by Driver and Meade (2019), these findings point to the usefulness of employing, whenever possible, micro-founded measures in macroeconomic forecast exercises also in the Italian case, as well as confirming the exceptional nature of the two investigated crisis episodes.

The remainder of this article is organized as follows. Section 2 presents the types of models used to forecast non-financial corporations' investment dynamics in Italy, with a particular focus on the VECM, which includes several proxies of uncertainty and various alternative measures of financial factors. Section 3 describes the dataset we compiled for the purpose of this paper. Section 4 contains the forecasting exercise and illustrates the results delivered by several cointegrated VECM specifications, compared with those of alternative time-series models. Section 5 concludes.

2   Forecasting models

In this section we sketch a variant of the empirical investment model first put forward in Giordano et al. (2019). The model is consistent with the flexible neoclassical theory of Hall and Jorgenson (1967), yet is extended to a multivariate setting to capture the dynamic linkages among real investment, output and the user cost of capital, as well as the feedback effects among these variables. The model also includes additional short-term drivers.

The unrestricted vector autoregression (VAR) model of order p is defined as follows:

$$\boldsymbol{A}(L)\boldsymbol{z}_t \;\; = \;\; \boldsymbol{a}_0 + \boldsymbol{\varepsilon}_t, \quad t = 1, \ldots, T, \tag{1}$$

where $\boldsymbol{z}_t$ is a vector of m endogenous I(1) variables in levels, $\boldsymbol{a}_0$ is an $m-$vector of intercepts, while $\boldsymbol{A}(L) = (\boldsymbol{I} - \boldsymbol{A}_1 L - \ldots - \boldsymbol{A}_p L^p)$ is a conformable matrix polynomial in

the lag operator L and $\boldsymbol{\varepsilon}_t$ is a vector of Gaussian white noise stochastic errors. Thus, in our sample $m = 3$ and $\boldsymbol{z}_t$ contains firms' real investment, real output and the real user cost of capital. These three series are found to be integrated of order one according to the two standard unit root/stationarity tests, the Augmented Dickey-Fuller test (Dickey and Fuller, 1979) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992), as shown in Appendix A.1. This result is quite standard in the empirical studies replicating the Hall and Jorgenson (1967) model, such as Bussière et al. (2015), Busetti et al. (2016) and Fatica (2018).[1]

The model in (1) can be rewritten as a VECM of order $p - 1$:

$$\Delta \boldsymbol{z}_t = \boldsymbol{a}_0 + \boldsymbol{\Pi} \boldsymbol{z}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{z}_{t-i} + \boldsymbol{\varepsilon}_t, \quad t = 1, \ldots, T - 1, \tag{2}$$

where $\Delta = (1 - L)$ is the differencing operator, $\boldsymbol{\Pi} = -\boldsymbol{A}(1) = -\left(\boldsymbol{I}_n - \sum_{i=1}^{p} \boldsymbol{A}_i \right)$ and $\boldsymbol{\Gamma}_i = -\sum_{j=i+1}^{p} \boldsymbol{A}_j$, for $(i = 1, \ldots, p - 1)$. Results, again reported in Annex A.1, point to the existence of a single cointegrating relationship linking firms' investment, output and the user cost of capital. A linear trend is also included in this cointegrating relationship, given that the real user cost of capital in particular displays a deterministic trend. Interest rates on bank loans indeed dramatically declined as a result of accession to the euro area; the real user cost of capital then started to creep up as of the mid–2000s, reaching its peak in connection with the outbreak of the global financial crisis. The overall expansionary monetary policy in the euro area contributed to dampen real interest rates thereafter, with rates currently more or less at their lowest levels since 1995, implying an overall marked downward trend.

Whenever $\boldsymbol{\Pi}$ has reduced rank ρ with $0 < \rho < m$, and ρ is the number of cointegrating

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[1] In particular, concerning the real user cost of capital, whereas the nominal interest rate is stationary, its other two components, namely inflation expectations and the depreciation rate of capital as will be discussed in Section 3, drive the I(1) process, according to further results available upon request.

relations, it is possible to decompose $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ (Johansen, 1995), leading to:

$$\Delta \boldsymbol{z}_t \;\; = \;\; \boldsymbol{a}_0 + \boldsymbol{\alpha}\boldsymbol{\beta}' \boldsymbol{z}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{z}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{3}$$

where $\boldsymbol{\alpha}$ is the matrix of loading factors that measure the speed of adjustment towards the long-run equilibrium relationships of the level variables, $\boldsymbol{\beta}$ is the matrix of cointegrating parameters and $\boldsymbol{\Gamma}_i$ are the matrices of parameters that capture short-run dynamics. If the k-th row of the loading matrix $\boldsymbol{\alpha}$ is zero, then there is no adjustment towards equilibrium and the k-th variable is defined as "weakly exogenous" (Engle et al., 1983), since it does not react to disequilibrium errors (but may still react to lagged changes of the endogenous variables).

Pesaran et al. (2000) show that it is possible to partition the m-vector $\boldsymbol{z}_t$ into an n-vector $\boldsymbol{y}_t$ of endogenous variables and a k-vector $\boldsymbol{x}_t$ of weakly exogenous variables, with $k := m - n$. After having conducted weak exogeneity tests described in Giordano et al. (2019) to which we refer, the final, full specification of the cointegrated VECM employed in this article includes three endogenous variables (investment, output and the user cost of capital, all expressed in real terms), as well as three additional weakly exogenous variables (business confidence, uncertainty and financial factors), which do not affect the long-run dynamics. We then estimate unrestricted VAR(p) models on these three variables. Several information criteria (Akaike, Schwarz, Hannan-Quinn) are employed to select the lag order p. There is no ambiguity in the results and two lags are retained ($p = 2$). Given that the series appear to have a trend, we assume a linear trend in the level data (unrestricted constant in the VECM) and in the cointegrating relations.

Consequently, the corresponding VECM representation in (2) can be rewritten as follows:

$$\Delta \boldsymbol{y}_t \;\; = \;\; \boldsymbol{c}_0 + \sum_{j=0}^{q-1} \boldsymbol{\Lambda}_j \Delta \boldsymbol{x}_{t-j} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i^{(y)} \Delta \boldsymbol{y}_{t-i} + \boldsymbol{\Pi}^{(y)} \boldsymbol{y}_{t-1} + \boldsymbol{u}_t, \tag{4}$$

where $\Delta \boldsymbol{y}_t$ is a vector containing log of investment $(\ln(I_t))$, log of output $(\ln(Y_t))$ and the user cost of capital (r_t), all expressed in real terms and in first differences, $\boldsymbol{c}_1 t$ is the linear trend, $\Delta \boldsymbol{x}_t = (\Delta confid_t, \Delta unc_t, \Delta fin_t)'$, $\boldsymbol{\Lambda}$ is a $k \times k$ matrix of short-run parameters of the $\boldsymbol{x}_t$ vector containing the weakly exogenous variables, $\boldsymbol{\Gamma}_i^{(y)}$ and $\boldsymbol{\Pi}^{(y)}$ are conformable $n \times n$ matrices, $q = 2$, $confid_t$ refers to business confidence, unc_t to uncertainty, and fin_t to financial factors.

As alternative models to the cointegrated VECM(1) model in the out-of-sample forecasting exercise, we also consider a VAR(2) as in equation (1), with three endogenous variables in log-levels (investment, output and the user cost of capital), as well as a VAR(1) model with the same three endogenous variables in first differences. The latter model omits the information on the cointegrating relationship and therefore is potentially misspecified.

In addition, we include two univariate models in the forecast horse-race and a further one as a robustness check, namely:

- an autoregressive model of order p (AR(p)) estimated on the quarterly growth rate of real investment $(\Delta \ln(I_t))$:

$$\phi_p(L)\Delta \ln(I_t) \quad = \quad c + \varepsilon_t, \quad \varepsilon_t \sim iid(0, \sigma_\varepsilon^2), \tag{5}$$

where the process $\{\varepsilon_t\}$ is an independent and identically distributed white noise with zero mean and constant variance equal to σ_ε^2, the stationary AR polynomial of order p is $\phi_p = 1 - \sum_{j=1}^p \phi_j L^j$, while the parameter c represents the constant term. The autoregressive order p is selected recursively, each time a new data point enters the information set, using the Schwarz information criterion (SIC) and assuming a maximum order of 4. This model is the simplest possible to forecast investment dynamics, and therefore represents our benchmark;

- an autoregressive moving average model (ARMA(p,q)), estimated on the quarterly growth rate of real investment:

$$\phi_p(L)\Delta \ln(I_t) \quad = \quad c + \theta_q(L)\varepsilon_t, \quad \varepsilon_t \sim iid(0, \sigma_\varepsilon^2), \tag{6}$$

where the invertible MA polynomial of order q is $\theta_q = 1 + \sum_{j=1}^{q} \theta_j L^j$. The autoregressive order p and the moving average order q are selected recursively using the SIC, with a maximum of 4 lags. Popularised by Box and Jenkins (1970), ARMA models have indeed become a benchmark for predicting economic variables and have been found to perform well in forecast comparison exercises (Marcellino et al., 2003).

- an autoregressive distributed lag (ARDL) model, again estimated on the quarterly growth rate of real investment. The model has an autoregressive component, in that the dependent variable is allowed to depend on its lagged values, and it also has a distributed lag component, in the form of successive lags of the regressors:

$$\phi_p(L)\Delta \ln(I_t) \quad = \quad c + \sum_{j=1}^{k} \beta_j(L)x_{j,t} + \varepsilon_t, \quad \varepsilon_t \sim iid(0, \sigma_\varepsilon^2), \tag{7}$$

where $\beta_j(L) = 1 + \sum_{l_j=1}^{s_j} \beta_{j,l_j} L^{l_j}$.

It is noteworthy that none of the competing models, with the exception of the ARDL model employed in the sensitivity analysis, include the short-run weakly exogenous variables employed in the fully-fledged cointegrated VECM.[2]

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[2]Seasonal ARMA models are not used given that seasonality has been removed by applying a one-sided 4-term moving average filter. Moreover, other nonlinear time-series models (Granger et al., 1993; Potter, 1999), such as a threshold autoregression model (Tsay, 1989) and a two-state Markov switching autoregressive model (Hamilton, 1989; Hamilton, 1994), were also considered for forecast comparison purposes. However, results, available upon request, were most of the times not satisfactory in the case under study.

3 The dataset

The quarterly dataset compiled to conduct our forecasting exercise is an update, refinement and expansion of that first employed in Giordano et al. (2019).

Real gross fixed capital formation of non-financial corporations, already plotted in Figure 1, is obtained by deflating nominal gross fixed capital formation with the total non-housing investment deflator. Real output is proxied by firms' value added, again computed at constant prices. The real user cost of capital is proxied by the sum of the real interest rate and the depreciation rate of capital, as in Bulligan et al. (2017). In turn, the real interest rate is computed as a weighted average of the short and long-term nominal bank lending rates to non-financial corporations, sourced from Banca d'Italia, net of one-year ahead inflation expectations, provided by Consensus Economics. The depreciation rate is calculated by dividing the amount of consumption of fixed capital of the non-financial private economy by the total gross capital stock net of residential construction. Seasonality is removed by using a moving average filter. Business confidence is measured by the economic sentiment indicator sourced from the monthly Istat Business Survey and then averaged over three months.

In order to measure uncertainty, we employ several proxies. The first two are total-economy or financial market measures, the third is a survey-based one. Economic policy uncertainty (EPU) is measured by the newspaper article count of the words "uncertainty" and similar (Baker et al., 2016), while global financial uncertainty is measured by the Chicago Board Options Exchange Volatility Index (VIX), sourced from Bloomberg. Following the recent empirical literature (Fuss and Vermeulen, 2008; Bachmann et al., 2013; Gamberoni et al., 2016; Busetti et al., 2016), we also compute the dispersion in the expectations of manufacturing firms interviewed in the afore-mentioned Istat survey. This measure is calculated as:

$$unc_t = \sqrt{frac_t^+ + frac_t^- - (frac_t^+ - frac_t^-)^2}, \tag{8}$$

Figure 2: **Uncertainty indices**
(standardised values)
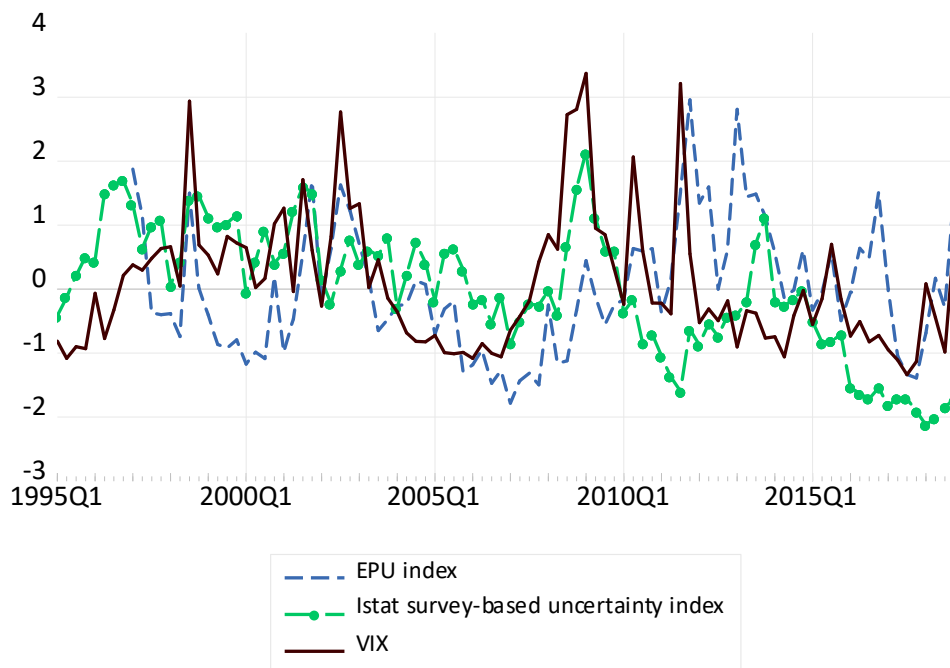
where $frac_t^+$ and $frac_t^-$ are the shares of firms at time t which expect their production activity to increase and to decrease, respectively, in the short term. In more detail, this measure is the cross-sectional standard deviation of firms' survey responses when the "increase" response is coded as 1, the neutral response of stationarity as 0 and the "decrease" response as -1; it hence varies between 0 and 1. The survey questions we consider are those referring to future production and orders relative to the current situation.[3] We then take quarterly averages of the mean of the two monthly dispersion measures.

All three indicators report striking peaks in uncertainty connected with major events, such as the burst of the dot.com bubble, the GFC and the SDC (Figure 2).[4]

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[3]For both questions the share of firms providing the neutral response is on average higher than 60 per cent over the period considered.

[4]In this figure the three measures are standardised in order to be comparable.

To measure financial factors, following Hall (2009), we first consider firms' debt-to-GDP ratio, where the numerator is retrieved from the Bank of Italy's financial accounts. In particular, debt includes the stock of short and long-term loans received and of securities issued by non-financial corporations. To measure debt build-up, we take the change in the corporate debt-to-GDP ratio over the previous three years.[5]

An issue with this proxy is that credit aggregates do not convey enough information to disentangle supply and demand (Bernanke and Gertler, 1989); the recent literature has therefore tried to improve identification using micro data. Following Guiso and Parigi (1999), Gaiotti (2013) and Giordano et al. (2019), we exploit direct, survey-based information on the limits of credit availability. Credit access conditions refer to the entire pool of possible borrowers and therefore these data are not subject to sample bias on granted loans as is the case for corporate debt data. In particular, we construct an indicator of borrowing constraints of both industrial (net of construction) and service firms based on data extracted from Banca d'Italia's Survey of Industrial and Service Firms (SISF, upper panel of Figure 3).[6] This variable is defined as the share of firms that were unable to obtain external finance from financial institutions out of all firms participating in the survey. Firms are "financially constrained" when either their loan request is (partially or totally) refused by the bank or the loan conditions are deemed to be excessive by the firm and therefore the loan is not extended. Even though this variable captures a "structural" feature of the Italian economy, which has been found to be significant in explaining corporate investment in this country, it has the drawback, however, of being available on a yearly basis. To address this issue, we temporally disaggregate the variable to obtain quarterly values by applying standard statistical techniques (i.e., the original Chow-Lin procedure as proposed by Chow and Lin, 1971), and then construct the build-up variable,

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[5]In the original model in Giordano et al. (2019) the deviation relative to the trend of corporate debt was employed. The forecasting ability of the corporate debt build-up variable is, however, generally higher and therefore only the latter measure is employed in this article for the sake of brevity.

[6]The SISF collects information on an annual basis from a large panel of Italian firms with more than 50 employees operating in both industry net of construction and services since 1972 and with more than 20 employees since 2002.
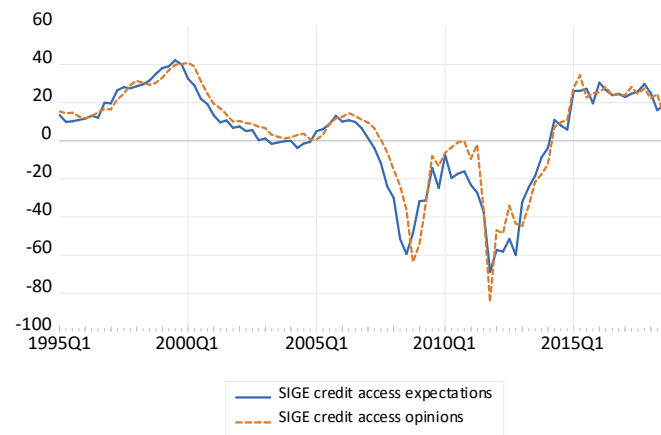
as for the debt-to-GDP ratio.

Figure 3: **Firms' financing constraint indicators**

(percentages for the debt-to-GDP ratio and the SISF indicator; standardised values for the reconstructed SIGE indicators)

(a) Debt-to-GDP ratio and SISF financing constraints' indicator
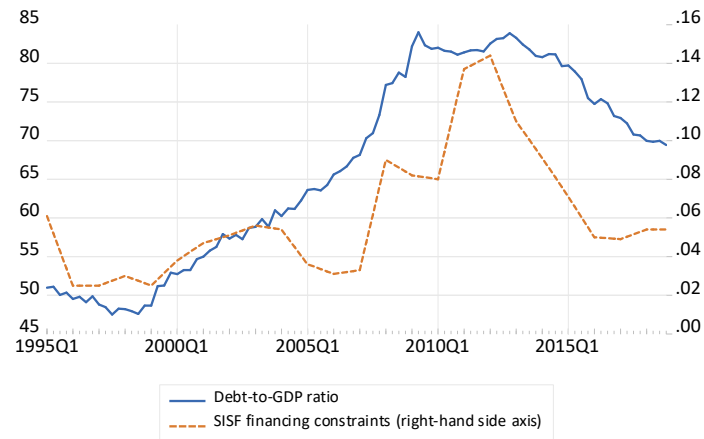
(b) Reconstructed SIGE indicators

Source: Authors' calculations on Istat and Banca d'Italia data.

We next consider two variables from the Banca d'Italia's quarterly Survey of Inflation and Growth Expectations (SIGE),[7] which provides qualitative information on firms' current and expected access to credit, respectively (lower panel of Figure 3). An increase in the SIGE variables indicates an improvement in credit conditions, and hence they are negatively correlated with the corporate debt and SISF variables. The issue with SIGE is that it is only available since 2009. In order to construct a longer series since 1995 we retropolated the SIGE variables backward with data on firms' opinions on cash availability with respect to their needs taken from Istat's afore-mentioned monthly Business Survey.[8] Finally, we constructed build-up measures, as for the other financial variables.

As shown in Figure 3, which plots all the financial indicators, it is quite straightforward to see the negative effects of the main financial crises in the period under study (the dot.com bubble, the GFC and the SDC), which all led to tighter financing constraints.

4   The forecasting set-up and results

4.1   Set-up and in-sample analysis

The aim of our forecasting exercise is to evaluate the relative forecasting performance of several cointegrated VECM specifications, augmented or not with one or all of the weakly exogenous variables described in the previous section, together with the other competing models referred to in Section 2. In total, there are eleven competing models. The target variable is firms' real investment growth rate at quarterly frequency. The time series are available from 1995Q1 through 2018Q4 (96 observations).[9] We also explore three different in-sample estimation windows (and corresponding out-of-sample forecasting periods) in

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[7]The SIGE is conducted on a panel of over 1,000 firms, with the aim of drawing qualitative information on firms' expectations about several economic variables such as inflation, investment, employment, credit access, etc.

[8]Since seasonally-adjusted data for this indicator are only available since 2000, we employed raw monthly data, available for a longer time-span, which we seasonally adjusted; we then took quarterly averages of monthly seasonally-adjusted data.

[9]Note that, relative to the series plotted in Figure 1, the observations until 1996:Q1 are lost because real GFCF and output are smoothed by a 4-period moving average filter to address seasonality issues.

order to assess changes in the forecasting ability of the selected models due to the inclusion or exclusion of one or both crisis episodes, as well as to specific quarters.

Before proceeding to the forecasting exercise, in Table 1 we report the estimation results of the cointegrated VECM specification including only the endogenous variables, estimated over the full period. The upper part of the table displays estimates of the exactly identified cointegrating vector, after the normalization procedure suggested by Johansen (1995). The lower part provides estimates of the speed of adjustment parameters and of the short-run dynamics.

Focusing on the GFCF equation, i.e. the first column, the estimated specification is: $\Delta(\ln(I_t)) = -0.1590(\ln(I_{t-1}) - 1.6195\ln(Y_{t-1}) + 0.1593r_{t-1} + 5.7091 + 0.0034t) + 0.0011 + 0.4241\Delta(\ln(I_{t-1})) + 0.6221\Delta(\ln(Y_{t-1})) + 0.0316\Delta(r_{t-1})$. Overall, the identified cointegrating vector confirms the long-run relationship between firms' real investment and its two standard determinants (real value added and real user cost of capital), supporting the validity of the flexible neoclassical model in the long run for Italian firms, as already documented in Giordano et al. (2019) over a shorter time-span. In particular, the long-run investment elasticity with respect to value added is highly significant and above unity. At the same time, our estimate of the negative investment elasticity to the real user cost of capital lies in the lower end of the range of the values found in the empirical literature for business investment (e.g., between -0.17 estimated for Italy by Bacchini et al., 2018, and -0.44 estimated for the UK by Ellis and Price, 2004).[10]

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[10]One plausible reason why firms' aggregate investment is not strongly responsive to the cost of capital, a result that was also found in Banerjee et al. (2015), is aggregation bias, due to the fact that different components of aggregate investment react differently to the cost of capital. In particular, Bacchini et al. (2018) find a significant negative long-run relationship between investment and the real user cost of capital for the non-ICT components of capital accumulation and a non-significant association for the ICT item. The fact that our results for firms' total capital expenditure accord with the flexible neoclassical model in the long run is plausibly due to the low share of ICT and intellectual property products investment in aggregate investment in Italy.

Table 1: **VECM estimates without exogenous variables over the full sample (1995Q1–2018Q4)**

	Coint. Equation		
$\ln(I_{t-1})$	1.0000		
$\ln(Y_{t-1})$	-1.6195***		
	[-10.0158]		
r_{t-1}	0.1593***		
	[5.3505]		
$Trend$	0.0034***		
	[9.4450]		
$Const.$	5.7091		
Error Correction:	$\Delta(\ln(I_t))$	$\Delta(\ln(Y_t))$	$\Delta(r_t)$
Speed of adj.	-0.1590***	-0.0573***	-0.2166
	[-5.6751]	[-4.0594]	[-1.2168]
$\Delta(\ln(I_{t-1}))$	0.4241***	0.1171*	0.2478
	[3.4355]	[1.8840]	[0.3158]
$\Delta(\ln(Y_{t-1}))$	0.6221**	0.4560***	0.1134
	[2.1383]	[3.1127]	[0.0613]
$\Delta(r_{t-1})$	0.0316*	0.0146	0.5664***
	[1.7785]	[1.6363]	[5.0169]
$Const.$	0.0011	0.0009*	-0.0064
	[1.0665]	[1.8199]	[-1.0055]
Adj. R-squared	0.7412	0.6864	0.3094
Log likelihood		818.2678	
Schwarz criterion		-17.8354	

Notes: t-statistics are in [ ]. ***, ** and * denote statistical significance at 1, 5 and 10%, respectively.

Turning to the lower panel of the table and hence the short-run dynamics, the speed of adjustment coefficient in the non-financial corporations' GFCF equation is both significant and negative, suggesting that in each period investment adjusts partially to its long-run equilibrium level (as do the other two endogenous variables). Lastly, most of

the short-run coefficients have significant coefficients and expected signs, especially in the investment and value added equations. The significant and positive role of lagged changes in GFCF in the first column could point, for example, to the lumpiness of investment. Overall, the investment equation performs well in-sample, as indicated by the adjusted R-squared (which is 0.74).

4.2 Out-of-sample forecast exercise

We can now turn to our forecasting exercise, which is conducted using an expanding window approach. The first in-sample period used for estimation ranges from 1995Q1 to 2008Q4, thereby covering the pre-GFC period. As a result, the out-of-sample validation sample goes from 2009Q1 to 2018Q4. The maximum forecast horizon is four quarters. Therefore, $h = 1, 2, 3, 4$-steps ahead forecasts are produced for 2009Q1, 2009Q2, 2009Q3 and 2009Q4, and forecast errors computed for each of the eleven models under scrutiny. Then, the in-sample period is expanded by one observation (thereby the end date of the in-sample becomes 2009Q1) and all the models are re-estimated, $h = 1, 2, 3, 4$-steps ahead forecasts are again produced, and the corresponding forecast errors calculated. When the forecast horizon is larger than one quarter, we compute dynamic forecasts, meaning that previously forecasted values of lagged investment are used for the predictions. When the cointegrated VECM specification contains exogenous variables, the latter are predicted by means of standard ARMA(p,q)/ARIMA(p,d,q) models, in which the orders are again recursively selected using the SIC (the maximum lag length considered for p and q is 4, whereas the integration order d is either 0 or 1). Recursive estimation (and forecasting) is performed for the number of quarters included in the evaluation period.

As is standard, the metric we employ to appraise the forecasting ability of the various models is the root mean-squared forecast error (RMSFE). For each prediction model,

forecast horizon and information set, the RMSFE is defined as:

$$RMSFE(h,j) \quad = \quad \sqrt{\frac{1}{N - t_0 + 1} \sum_{t=t_0}^{N} (y_{t+h} - \hat{y}_{t+h|t}^{j})^2} \tag{9}$$

where y_{t+h} is the realized value of the target variable (quarter-on-quarter investment growth rate) at time $t + h$, t_0 and N are the first and last data point in the out-of-sample, $\hat{y}_{t+h|t}^{j}$ is the forecast made at time t at horizon h from model j (Hyndman et al., 2008). Moreover, we employ the Diebold and Mariano (1995) statistic to test for equal forecasting accuracy of a given model relative to a benchmark model (namely, the AR(p) model).[11]

Concerning one-step ahead forecasts (upper panel of Figure 4), cointegrated VECMs provide higher predictive accuracy relative to AR, ARMA or VAR models only when they are augmented with weakly exogenous variables that capture the business climate, uncertainty and financial factors. In particular, the SISF measure of financing constraints is superior to the other financial proxies, leading to a lower RMSFE. Moreover, there is apparently no significant difference between the VECM specification including the survey-based uncertainty measure and that including the EPU index. All these results hold for four-step ahead forecasts too for which, as to be expected, RMSFEs are higher across the board (lower panel of Figure 4), with the exception that the EPU index appears to have a slightly better forecasting ability than the micro-founded uncertainty proxy.[12] In a sensitivity check, we find that these results are also confirmed by allowing the out-of-sample period to start in 2009Q1, 2009Q2 and 2009Q3 (Figure A.4 in Appendix A.2). Moreover, in the upper panel of Figure A.5, focused for brevity only on four-step ahead forecast and a selection of four models, we report forecast errors of investment dynamics on a quarterly basis. All models bar the VAR(2) perform badly (i.e., the forecast errors

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[11]See Busetti and Marcucci (2013) for further details.

[12]For the sake of brevity, we here focus on one-step-ahead and four-step ahead forecasts. Two-step ahead and three-step ahead forecast exercises are reported in the Appendix A.2 (Figures A.1, A.2 and A.3) and support the evidence provided herein.

were highest) in the prediction of the GFC and the subsequent recovery, yet less so in the prediction of the SDC, where instead the VAR(2) performs worst. In general, the specification augmented with the survey-based measures of business climate, uncertainty and financial constraints (sourced from SISF) displays amongst the lowest forecast errors in all years excluding the GFC.
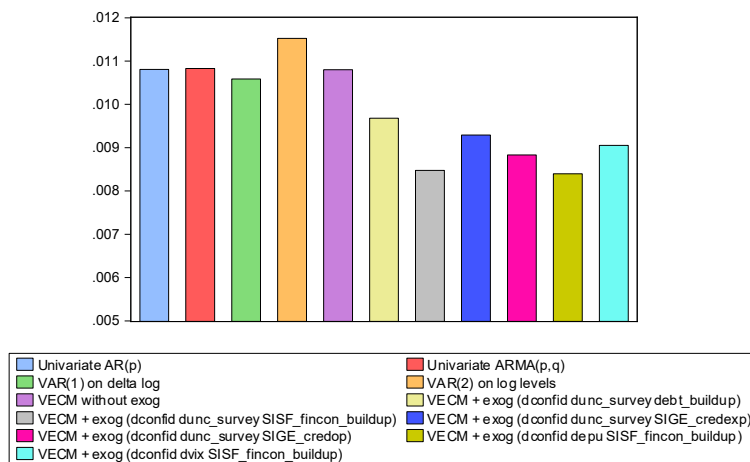
In order to assess the effect of the sample period on forecast evaluation, in the second forecasting exercise we expand the starting in-sample estimation window by eight quarters and repeat estimation and forecasting in a similar way. As a result, the in-sample estimation period covers the 1995Q1–2010Q4 time span, including 2009Q1 and 2010Q2, broadly including the beginning and end of the GFC, while the out-of-sample period is 2011Q1–2018Q4. We generate out-of-sample forecasts one through four quarters ahead and compare the root-mean-squared forecast errors from the cointegrated VECM specifications to those from standard time-series models.

By incorporating the GFC in the in-sample estimation period (Figure 5), RMSFEs drop across the board, underlying the highly exceptional nature of this crisis episode, and the difficulty of predicting firms' investment dynamics based on pre-crisis historical data. Again, the cointegrated VECM augmented with the SISF financing-constraint variable performs well both in the one-step ahead exercise and, especially, in the four-step ahead one, relative to the other specifications. Concerning the best proxy of uncertainty, the specification that includes the survey-based measure turns out to have the lowest RMSE, suggesting that whether in "normal" times this micro-founded indicator and the EPU index were broadly equivalent in forecasting ability terms, during the GFC firms' demand uncertainty captured by the first proxy was more accurate in predicting corporate investment behaviour.
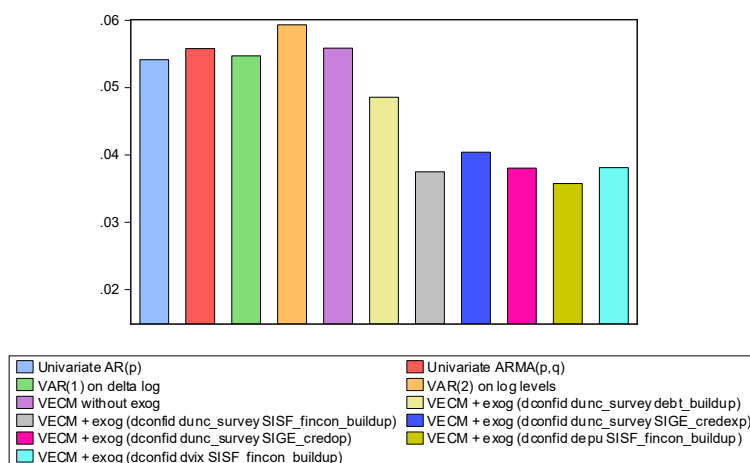
Finally, by also including the SDC period in the in-sample estimation window, and hence by restricting the evaluation period to 2013Q1–2018Q4 in our third exercise, RMS-FEs fall even further in most specifications (Figure 6). This is particularly true for the

Figure 4: **Average RMSFE results across 1-step and 4-step ahead forecasts**
(recursive estimation, out-of-sample 2009Q1–2018Q4)
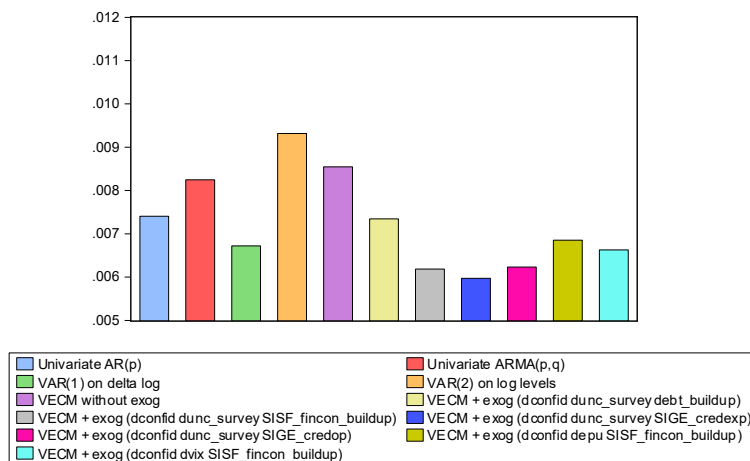

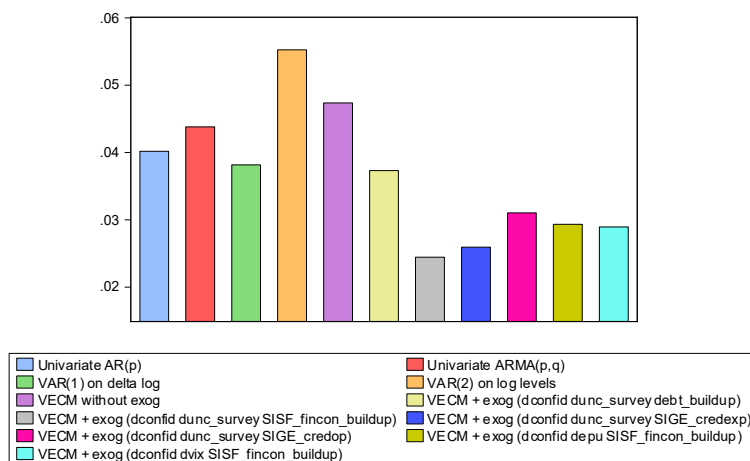(a) one-step ahead

(b) four-step ahead

Notes: The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

VECMs which include the SISF financial indicator. The superiority of the VECM specification augmented with the survey-based uncertainty measure and the SISF financial constraint indicator is also confirmed when investigating forecast errors of the investment growth rate on a quarterly basis (lower panel of Figure A.5), in that this model displays the lowest errors in nearly all years. Returning to Figure 6, also the two specifications containing firms' opinions on credit access, as measured by the SIGE perform well.

Figure 5: **Average RMSFE results across 1-step and 4-step ahead forecasts**

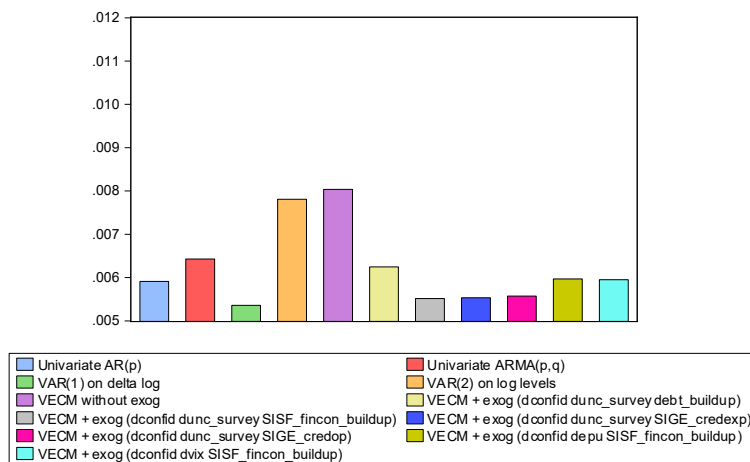*(recursive estimation, out-of-sample 2011Q1–2018Q4)*
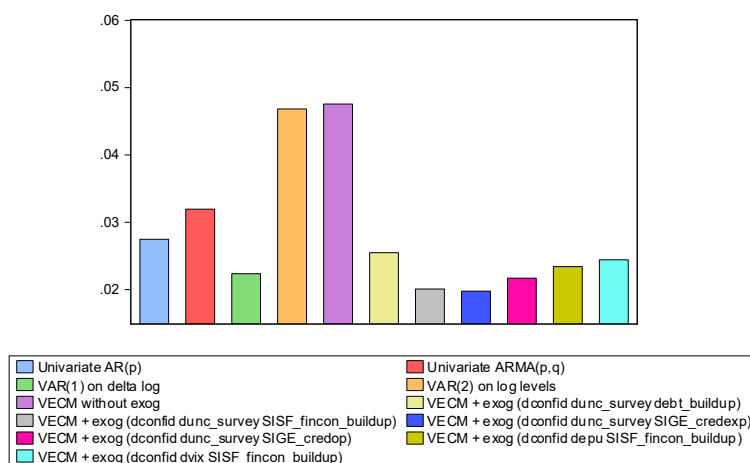

(a) one-step ahead

(b) four-step ahead

Notes: The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

Figure 6: **Average RMSFE results across 1-step and 4-step ahead forecasts**

(recursive estimation, out-of-sample 2013Q1–2018Q4)

(a) one-step ahead

(b) four-step ahead

Notes: The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

Tables 2-4 formalise the results discussed so far, by providing the RMSFE ratio of each competing model relative to the AR(p) on the three evaluation samples and by highlighting the results of a Diebold and Mariano (1995) test for the null of equal forecast accuracy between a given model and the AR(p) model.[13] By construction, a number smaller (larger) than one indicates that a model performs better (worse) than the AR model in terms of RMSFE. Moreover, the figures highlighted in bold imply rejection of the null hypothesis of equal forecast accuracy. Finally, the grey shaded areas highlight the model which presents the minimum RMSFE ratio at each forecast horizon and which also passes the Diebold-Mariano test.

As suggested visually by the previous figures, when the full evaluation sample is considered, the VECM specification augmented with business confidence, the EPU index and the SISF financial-constraint variable presents the highest forecasting ability, from the second-step ahead forecast onwards. For the one-step ahead projections, there is no significant difference between forecast models according to the Diebold-Mariano test. In Appendix A.3 we show that even when considering a univariate ARDL model, with and without financial factors, the specification that includes the SISF proxy outperforms all others, according to the Diebold-Mariano test. In turn, we also show how the corresponding VECM outperforms the ARDL, confirming that the multivariate model is better than the univariate one for forecasting non-financial corporations' investment dynamics.

By incorporating first the GFC episode and then also the SDC episode in the in-sample estimation window, the VECM that includes the survey-based uncertainty proxy turns out to be the best performer in predicting corporate investment dynamics in Italy again from the second or more step-ahead forecasts, together with one of the three survey-based financial measures. In the first-step ahead projection of Table 3 and in the first- and second-step ahead projections of Table 4, no model jointly passes the Diebold-

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[13]As a robustness check, following Harvey et al. (1997), we also run a modified Diebold-Mariano test using a small-sample bias corrected variance calculation. Test results, available from the authors upon request, are in line with those obtained by employing the standard Diebold-Mariano test.

Mariano test and displays an RMSFE that is lower than that of the benchmark AR(p) model. This implies that the survey-based indicators employed in this paper significantly contribute to forecasting investment, albeit with a short lag.

Table 2: Forecast Performance: Evaluation sample 2009Q1–2018Q4

Model	1-step ahead	2-steps ahead	3-steps ahead	4-steps ahead
Univariate ARMA(p,q)	1.0021	1.0231	1.0260	1.0307
VAR(1) on delta log	0.9794	0.9953	1.0062	1.0106
VAR(2) on log levels	1.0664	1.0927	1.0953	1.0957
VECM without exog	0.9992	1.0164	1.0231	1.0319
VECM + exog (dconfid dunc_survey debt_buildup)	0.8956	0.8565	0.8773	0.8972
VECM + exog (dconfid dunc_survey SISF_fincon_buildup)	0.7842	**0.7392**	**0.7193**	**0.6929**
VECM + exog (dconfid dunc_survey SIGE_credexp)	0.8597	**0.8023**	**0.7792**	**0.7465**
VECM + exog (dconfid dunc_survey SIGE_credop)	0.8164	0.7592	0.7323	0.7015
VECM + exog (dconfid depu SISF_fincon_buildup)	0.7771	0.7164	0.6861	0.6605
VECM + exog (dconfid dvix SISF_fincon_buildup)	0.8374	0.7711	0.7357	0.7040

Notes: The table reports the ratios of each competing model's RMSFE to the RMFSE of an AR(p) model, at each forecast horizon ($h = 1, 2, 3, 4$). The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).
Numbers in bold and underlined indicate rejection at the 5% significance level of the Diebold-Mariano test for the null of equal forecast accuracy between the competing model and the AR model. The grey shaded areas highlight the model with the minimum RMSFE ratio at each forecast horizon and for which the null of the Diebold-Mariano test is rejected.

Table 3: Forecast Performance: Evaluation sample 2011Q1–2018Q4

Model	1-step ahead	2-steps ahead	3-steps ahead	4-steps ahead
Univariate ARMA(p,q)	1.1137	1.1043	1.0946	1.0900
VAR(1) on delta log	0.9078	0.9157	0.9386	0.9498
VAR(2) on log levels	**1.2580**	**1.3711**	**1.3827**	**1.3752**
VECM without exog	1.1545	1.2064	1.1958	1.1784
VECM + exog (dconfid dunc_survey debt_buildup)	0.9904	0.9412	0.9365	0.9289
VECM + exog (dconfid dunc_survey SISF_fincon_buildup)	0.8356	**0.7254**	**0.6572**	**0.6087**
VECM + exog (dconfid dunc_survey SIGE_credexp)	0.8068	**0.7182**	**0.6793**	**0.6455**
VECM + exog (dconfid dunc_survey SIGE_credop)	0.8395	0.7826	0.7753	0.7697
VECM + exog (dconfid depu SISF_fincon_buildup)	0.9257	0.8265	0.7683	0.7300
VECM + exog (dconfid dvix SISF_fincon_buildup)	0.8953	0.8106	0.7554	0.7206

Notes: The table reports the ratios of each competing model's RMSFE to the RMFSE of an AR(p) model, at each forecast horizon ($h = 1, 2, 3, 4$). The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).
Numbers in bold and underlined indicate rejection at the 5% significance level of the Diebold-Mariano test for the null of equal forecast accuracy between the competing model and the AR model. The grey shaded areas highlight the model with the minimum RMSFE ratio at each forecast horizon and for which the null of the Diebold-Mariano test is rejected.

Table 4: Forecast Performance: Evaluation sample 2013Q1–2018Q4

Model	1-step ahead	2-steps ahead	3-steps ahead	4-steps ahead
Univariate ARMA(p,q)	1.0873	1.1291	1.1651	1.1627
VAR(1) on delta log	0.9069	0.8531	**0.8274**	**0.8140**
VAR(2) on log levels	**1.3212**	1.5836	1.6677	1.7041
VECM without exog	1.3596	**1.5965**	**1.6835**	**1.7302**
VECM + exog (dconfid dunc_survey debt_buildup)	1.0536	1.0148	0.9701	0.9268
VECM + exog (dconfid dunc_survey SISF_fincon_buildup)	0.9331	0.8789	0.7989	**0.7318**
VECM + exog (dconfid dunc_survey SIGE_credexp)	0.9363	0.8584	0.7789	0.7194
VECM + exog (dconfid dunc_survey SIGE_credop)	0.9425	0.8828	**0.8151**	**0.7899**
VECM + exog (dconfid depu SISF_fincon_buildup)	1.0098	0.9748	0.9150	0.8526
VECM + exog (dconfid dvix SISF_fincon_buildup)	1.0065	1.0007	0.9507	0.8894

Notes: The table reports the ratios of each competing model's RMSFE to the RMFSE of an AR(p) model, at each forecast horizon ($h = 1, 2, 3, 4$). The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in log levels, VAR(2) on the three endogenous variables in first differences, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).
Numbers in bold and underlined indicate rejection at the 5% significance level of the Diebold-Mariano test for the null of equal forecast accuracy between the competing model and the AR model. The grey shaded areas highlight the model with the minimum RMSFE ratio at each forecast horizon and for which the null of the Diebold-Mariano test is rejected.

5   Conclusions

Forecasting non-financial corporations' investment dynamics in Italy is not an easy task, as proven by the significant forecasting errors when the in-sample estimation window coincides with the period prior to 2009. However, results show that a cointegrated VECM, which extends the flexible neoclassical model put forward by Hall and Jorgenson (1967), to include multivariate feedback effects between the three main endogenous variables – firms' real investment, real output and real user of capital – as well as the contribution of three weakly exogenous variables, namely business confidence, uncertainty and financial factors, outperforms a series of alternative time-series model in forecasting investment dynamics in Italy. The above-mentioned VECM model is the best model only when financial factors are proxied by survey-based measures and when uncertainty is measured by a micro-founded indicator of firms' demand uncertainty, especially when the in-sample estimation period covers both the GFC and the SDC and when two or more step-ahead forecasts are considered.

These findings confirm the value added of exploiting survey data in macroeconomic analyses and forecasting exercises, whenever possible, especially in the case of extreme shocks. The advantage in the case of Italy is the regular availability and easy access of the surveys employed in this paper. Future research could hence be directed to the impact of survey-based information on the accuracy of corporate investment forecasting in relation the most recent, dramatic recession linked to the COVID-19 pandemic, which broke out at the time of writing of this article.

A APPENDIX

A.1 Unit root and cointegration tests

In this appendix we report the results of standard unit root or stationarity tests for the three endogenous variables (real investment, real output and the real user cost of capital, all referred to non-financial corporations) of the VECM defined in Section 2, over the whole period under study. The null hypothesis of the Augmented Dickey-Fuller (ADF) test is the presence of a unit root (Dickey and Fuller, 1979). Regressions are run with both an intercept and a linear time trend. The ADF test is, however, often criticised for its low power in rejecting the null hypothesis, especially when the sample size is small. To overcome this problem, unit root tests are often complemented with stationarity tests, such as the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). The outcomes of the ADF and KPSS tests for real investment, real output and the real user cost of capital are presented in Tables A.1 and A.2. The reported critical values for the ADF tests are obtained from MacKinnon (1996), whereas those for the LM test statistic of the KPSS test are based upon the asymptotic results presented in Kwiatkowski et al. (1992).

ADF test results imply acceptance of the presence of a unit root for the series under study at the 10 per cent significance level. A similar outcome is confirmed by the KPSS test: the null hypothesis of stationarity is rejected at the 5 per cent significance level. We therefore conclude that all variables under consideration are non-stationary, and in particular I(1), i.e. stationary after first differencing.[14] This finding enables us to proceed to testing the existence of cointegrating relationships using the methodology developed by Johansen (1995).

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[14]Unit root test were indeed run also on first differences of the three variables under analysis, hence confirming their I(1) nature. Results are available upon request.

Table A.1: **ADF unit root tests over the full sample (1995Q1–2018Q4)**

ADF unit root test on $\ln(I_t)$		
Null Hypothesis: $\ln(I_t)$ has a unit root		
Exogenous: Constant, Linear Trend		
		t-Stat.
ADF test		-3.2227
Test critical values[*]	1% level	-4.0670
	5% level	-3.4623
	10% level	-3.1575

ADF unit root test on $\ln(Y_t)$		
Null Hypothesis: $\ln(Y_t)$ has a unit root		
Exogenous: Constant, Linear Trend		
		t-Stat.
ADF test		-3.2895
Test critical values[*]	1% level	-4.0670
	5% level	-3.4623
	10% level	-3.1575

ADF unit root test on r_t		
Null Hypothesis: r_t has a unit root		
Exogenous: Constant, Linear Trend		
		t-Stat.
ADF test		-3.5167
Test critical values[*]	1% level	-4.0586
	5% level	-3.4583
	10% level	-3.1552

[*] MacKinnon (1996) critical values.

Table A.2: **KPSS tests over the full sample (1995Q1–2018Q4)**

KPSS stationarity test on $\ln(I_t)$	
Null Hypothesis: $\ln(I_t)$ is stationary	
Exogenous: Constant, Linear Trend	
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel	
	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.2083
Asymptotic critical values[*] 1% level	0.2160
5% level	0.1460
10% level	0.1190

KPSS stationarity test on $\ln(Y_t)$	
Null Hypothesis: $\ln(Y_t)$ is stationary	
Exogenous: Constant, Linear Trend	
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel	
	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.1805
Asymptotic critical values[*] 1% level	0.2160
5% level	0.1460
10% level	0.1190

KPSS stationarity test on r_t	
Null Hypothesis: r_t is stationary	
Exogenous: Constant, Linear Trend	
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel	
	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.1841
Asymptotic critical values[*] 1% level	0.2160
5% level	0.1460
10% level	0.1190

[*] Kwiatkowski et al. (1992, Table 1).

In detail, we run a cointegration test, whose purpose is to determine whether the three non-stationary series (investment, value added and user cost of capital) are cointegrated. As discussed in Section 2, given that the series appear to have a trend, we assume a linear

deterministic trend in the cointegrating relations. Results are shown in Table A.3. The null hypothesis that there is no cointegrating relationship is rejected by both the trace test, while the hypothesis that there is one cointregrating relationship cannot be rejected at the 5 per cent significance level. Therefore, we conclude that firms' investment, value added and the user cost of capital share one cointegrating relationship.

Table A.3: **Cointegration rank test of real investment, real output and the real user cost of capital over the full sample (1995Q1–2018Q4)**

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of cointegrating equation(s)	Eigenvalue	Trace Statistic	Critical Value (5% significance level)	Prob.**
None *	0.2812	46.4534	42.9153	0.0213
At most 1	0.1354	17.7254	25.8721	0.3627
At most 2	0.0566	5.0695	12.5180	0.5864

Trend assumption: Linear deterministic trend (restricted)
* denotes rejection of the null hypothesis at the 5 per cent significance level
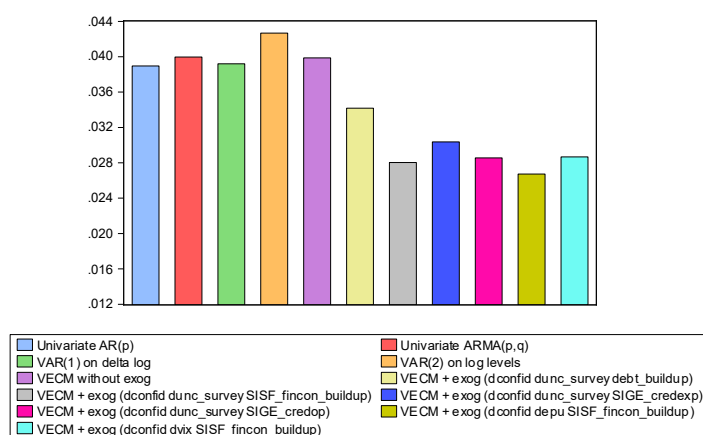** MacKinnon et al. (1999) p-values.

A.2 Alternative in-sample and out-of-sample periods and forecast errors

This appendix first contains figures illustrating additional out-of-sample forecast results of the exercise presented in the main text. Whereas in the latter the focus is on one-step ahead and four-step ahead forecasts, here we present two-step and three-step ahead results (Figures A.1, A.2 and A.3). It also provides a sensitivity analysis relative to one-step ahead forecasts over the 2009Q1–2018Q4 out-of-sample evaluation period (Figure A.4). Next, this appendix provides four-step-ahead forecast errors of four selected models and for two out-of-sample periods, namely those including and excluding the two crisis episodes analysed in the paper, for each quarter (Figure A.5).

Figure A.1: **Average RMSFE results across 2-step and 3-step ahead forecasts**

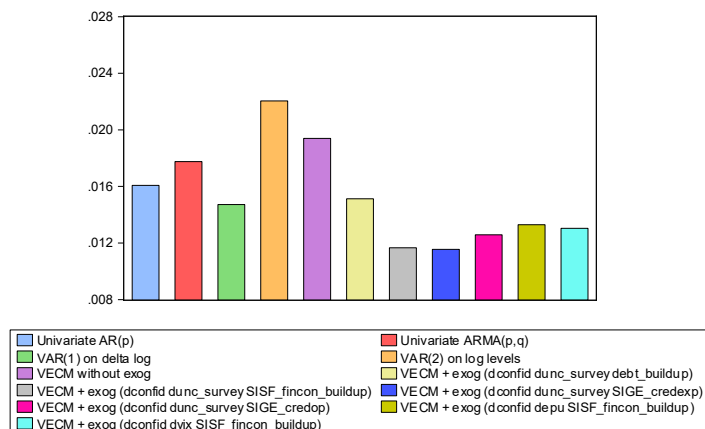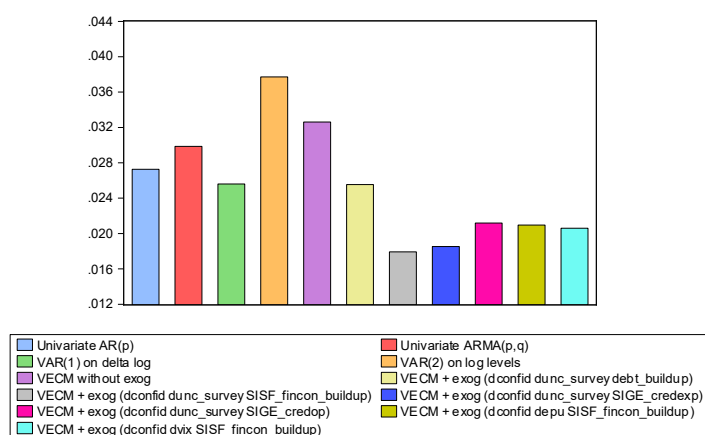*(recursive estimation, out-of-sample 2009Q1–2018Q4)*

(a) two-step ahead

(b) three-step ahead

Notes: The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

Figure A.2: **Average RMSFE results across 2-step and 3-step ahead forecasts**
(recursive estimation, out-of-sample 2011Q1–2018Q4)
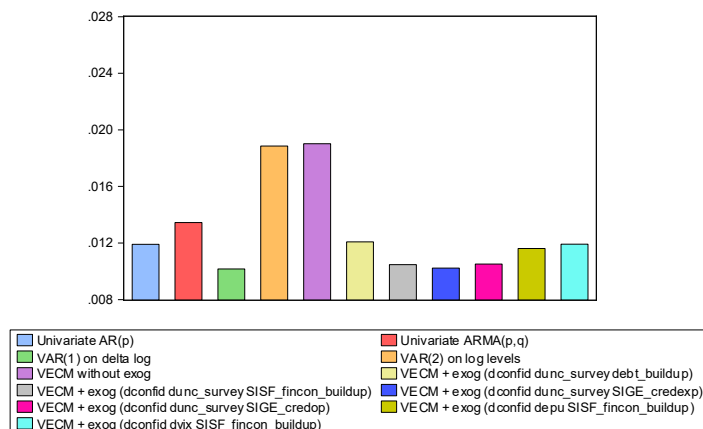

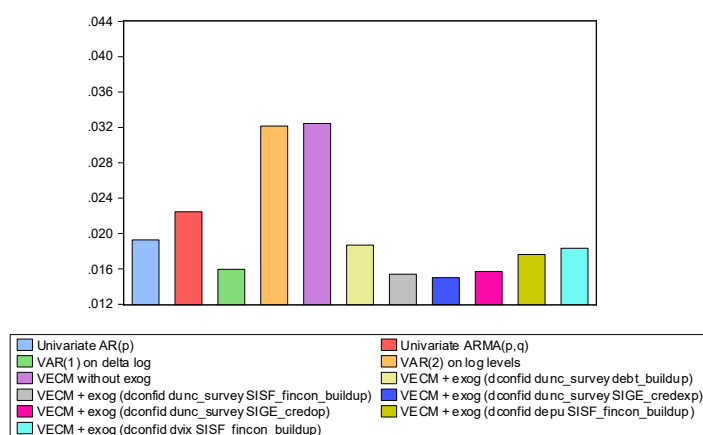(a) two-step ahead

(b) three-step ahead

Notes: The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

Figure A.3: **Average RMSFE results across 2-step and 3-step ahead forecasts**

(recursive estimation, out-of-sample 2013Q1–2018Q4)
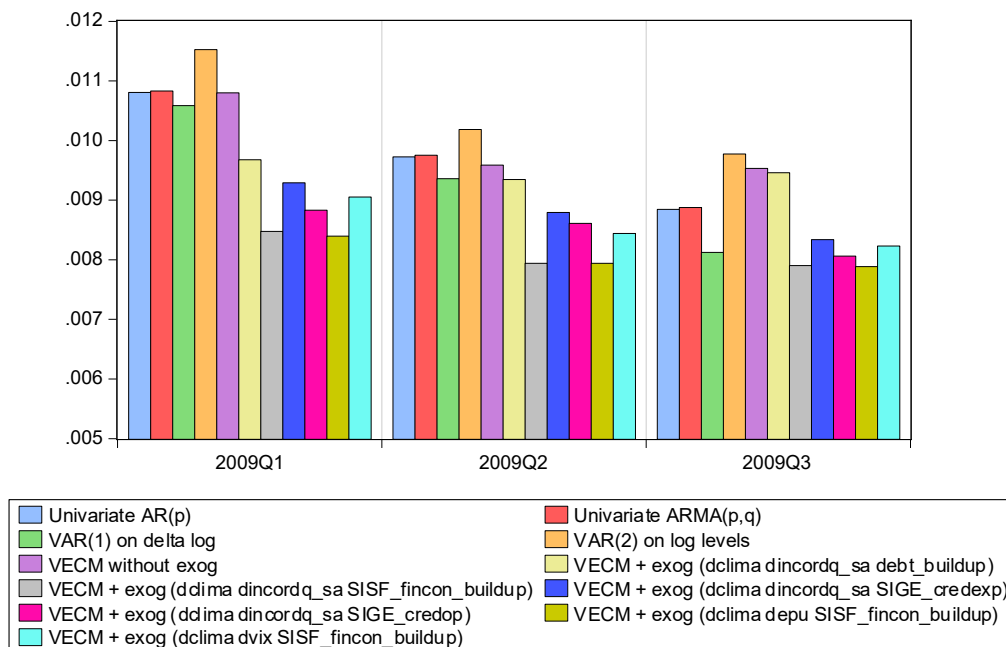

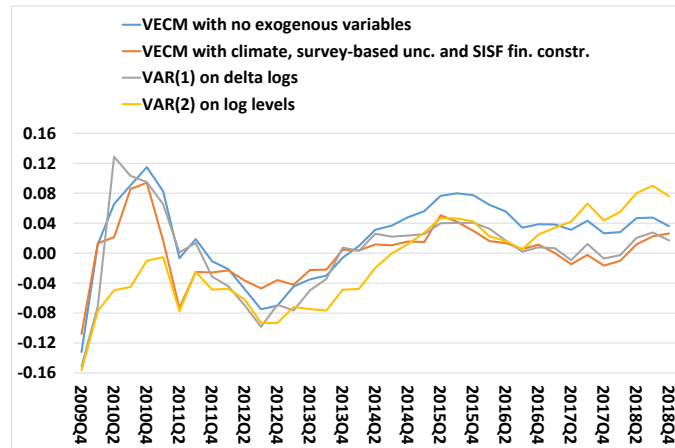(a) two-step ahead

(b) three-step ahead

Notes: The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

Figure A.4: **Average RMSFE results across 1-step ahead forecasts and three out-of-samples starting in 2009Q1, 2009Q2, 2009Q3**


Notes: Three different out-of-samples periods are considered in this exercise: 2009Q1–2018Q4, 2009Q2–2018Q4, and 2009Q3–2018Q4. The competing models are: univariate AR(p) and ARMA(p,q), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels, VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $debt\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credexp$), VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SIGE\_credop$), VECM with three weakly exogenous variables ($\Delta confid$, Δepu, $SISF\_fincon\_buildup$), VECM with three weakly exogenous variables ($\Delta confid$, Δvix, $SISF\_fincon\_buildup$).

Figure A.5: **Four-step ahead forecast errors of out-of-sample predictions**
(recursive estimation)

(a) 2009Q1-2018Q4
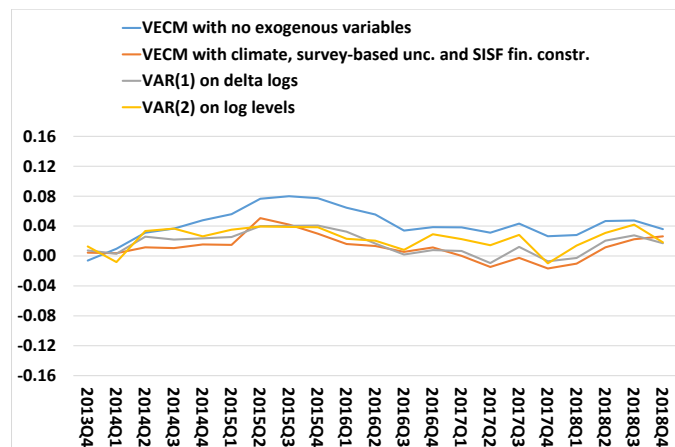
(b) 2013Q1-2018Q4

Notes: Forecast errors are displayed for the following competing models: VECM without weakly exogenous variables, VECM with three weakly exogenous variables ($\Delta confid$, Δunc_survey, $SISF\_fincon\_buildup$), VAR(1) on the three endogenous variables in first differences, VAR(2) on the three endogenous variables in log levels.

A.3 An alternative dynamic specification and its forecast performance: the ARDL model

This appendix examines whether, in a simple univariate ARDL context, the SISF financial-constraint build-up indicator provides any forecasting gains in predicting investment relative to alternative financial proxies; it then compares the forecasts produced by the best ARDL specification – which contains the SISF variable – with those delivered by a cointegrated VECM model with exogenous variables as in euqation (4), featuring the same financial indicator. Statistical significance of any differences in relative accuracy is assessed using Diebold-Mariano forecast comparison tests.

Four ARDL models as in equation (7) are considered. They all contain the growth rate of real investment and value added, the real interest rate, uncertainty (in first differences) and the business climate (in first differences). They only differ according to the financial variable included: the first ARDL model contains *debt_buildup* (ARDL 1), the second ARDL model $SIGE\_credop$ (ARDL 2), the third ARDL model $SIGE\_credexp$ (ARDL 3), while the fourth ARDL model incorporates $SISF\_fincon\_buildup$ (ARDL 4). All the ARDL specifications comprise up to one lag of real investment and up to one lag of the explanatory variables. The best specification is selected automatically for each model based on information criteria (AIC or BIC). As a benchmark model, we also rely on a cointegrated VECM with exogenous variables (uncertainty, business confidence and the SISF financial-constraints proxy). We perform two out-of-sample forecast exercises.

In the first exercise, we estimate all models over the full sample 1995Q1–2008Q4 and use 2009Q1 through 2018Q4 as the forecast evaluation period. For the sake of brevity, we here focus only on one-step ahead forecasts. The outcome is presented in Table A.4, which shows the test results of the Diebold-Mariano statistics of predictive ability, together with the corresponding p-values. According to the Diebold-Mariano test, there are no significant differences among the four ARDL models, except between the ARDL with the debt build-up variable and the ARDL with the SIGE financial-constraint variable, which

is the preferred one. This latter model, however, is in turn significantly outperformed by the multivariate VECM model with the survey-based SISF financial-constraints build up variable.

Table A.4: One-step ahead Forecast Performance: Diebold-Mariano tests
(out-of-sample 2009Q1–2018Q4)

	ARDL 1 vs ARDL 4	ARDL 2 vs ARDL 4	ARDL 3 vs ARDL 4	VECM with exog. vs ARDL 4
Diebold-Mariano	**<u>4.2040</u>**	0.3854	-0.6217	**<u>-4.0379</u>**
p-value	*0.0000*	*0.3500*	*0.2671*	*0.0000*

Notes: All ARDL models include the growth rate of real investment and value added, the real interest rate, uncertainty (in first differences) and the business climate (in first differences). These four ARDL models only differ according to the financial variable included: ARDL 1 contains *debt_buildup*, ARDL 2 contains $SIGE\_credop$, ARDL 3 contains $SIGE\_credexp$, while ARDL 4 includes $SISF\_fincon\_buildup$. Diebold-Mariano tests are used to compare alternative predictions. Numbers in bold and underlined indicate rejection at the 5% significance level of the Diebold-Mariano test for the null of equal forecast accuracy between the competing model and the ARDL 4 model.

In the second exercise, we examine whether there are any changes in the results when considering recursive forecasts, i.e., when re-estimating the parameters in the models for each quarter in the forecast evaluation sample. The focus is again on one-step ahead forecasts. Results are presented in Table A.5. In this case the two ARDL models with the SIGE indicators are outperformed by the ARDL model with the SISF proxy. Again, the cointegrated VECM model with the SISF financial-constraints build-up variable is on average more accurate than the corresponding ARDL model.

Table A.5: One-step ahead Forecast Performance: Diebold-Mariano tests
(recursive estimation, out-of-sample 2009Q1–2018Q4)

	ARDL 1 vs ARDL 4	ARDL 2 vs ARDL 4	ARDL 3 vs ARDL 4	VECM with exog. vs ARDL 4
Diebold-Mariano	0.8823	**3.8622**	**3.7749**	**-2.6714**
p-value	*0.1888*	*0.0000*	*0.0000*	*0.0038*

Notes: All ARDL models include the growth rate of real investment and value added, the real interest rate, uncertainty (in first differences) and the business climate (in first differences). These four ARDL models only differ according to the financial variable included: ARDL 1 contains $debt\_buildup$, ARDL 2 contains $SIGE\_credop$, ARDL 3 contains $SIGE\_credexp$, while ARDL 4 includes $SISF\_fincon\_buildup$. Diebold-Mariano tests are used to compare alternative predictions. Numbers in bold and underlined indicate rejection at the 5% significance level of the Diebold-Mariano test for the null of equal forecast accuracy between the competing model and the ARDL 4 model.

Overall, our conclusion from these additional exercises is that multivariate VECM models lead to more accurate one-step ahead forecasts compared to univariate ARDL models, even when the same set of variables is included. In this respect, it appears very important to acknowledge the role of cointegration in producing forecasts. In particular, ARDL models are generally worst forecasters than cointegrated VECM models according to the Diebold-Mariano test statistics (Ghysels and Marcellino, 2018); we confirm this result also for Italy's investment dynamics.

Acknowledgements

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