CEP 17-13

Does Business Confidence Matter for Investment?

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21 December 2017; revised 20 March 2019

CARLETON ECONOMIC PAPERS

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March 20, 2019

Abstract

Business confidence is a well-known leading indicator of future output. Whether it has information about future investment is, however, unclear. We determine how informative business confidence is for investment growth independently of other variables using US business confidence survey data for 1955Q1–2016Q4. Our main findings are: (i) business confidence has predictive ability for investment growth; (ii) remarkably, business confidence has superior forecasting power, relative to conventional predictors, for investment downturns over 1–3 quarter forecast horizons and for the sign of investment growth over a 2–quarter forecast horizon; and (iii) exogenous shifts in business confidence reflect short-lived non-fundamental factors, consistent with the 'animal spirits' view of investment. Our findings have implications for improving investment forecasts, developing new business cycle models, and studying the role of social and psychological factors determining investment growth.

Key words: Business confidence, Investment, Forecasting, Downturns, Directional forecasts

JEL Classification: C32, E22, E32, E37

*We thank three anonymous referees, Patrick Coe, Lilia Karnizova, Lynda Khalaf, Konstantinos Metaxoglou and participants at the Canadian Economic Association Conference, 2017 at Antigonish, Nova Scotia for comments.
Declaration of Interests: None.

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1 Introduction

Business confidence is a well-known leading indicator of future output, especially during economic downturns, and receives attention from the media, policymakers and forecasters. Somewhat surprisingly, the direct link between business confidence and investment has not yet been investigated. Our paper fills this gap. We provide a quantitative assessment of the information in business confidence for future investment growth, after controlling for the conventional determinants such as user cost, output, cash flow and stock price.

Understanding the predictive power of business confidence is valuable along three dimensions. First, it can help forecasters and policymakers improve their investment forecasts. Second, it can provide a rationale for explicitly including business confidence—either as causal or as anticipatory—in theoretical models of business cycles. Third, it can help motivate studies on the how investment managers' social and psychological circumstances influence investment decisions over and beyond rational cost-benefit analyses.[1]

We consider the Organization for Economic Co-Operation and Development (OECD)'s business confidence index for the US as a measure of business confidence and ask the following three questions.[2] Does business confidence have independent information about future business investment growth? Does it have forecasting power for investment downturns? Does it help in making directional forecasts—the positive or negative movements in the trajectory of investment growth?

Previous literature that used business confidence has primarily studied its predictive properties for variables other than investment. Heye (1993) examines the relationship between business confidence and labour market conditions in the US and other industrialized countries. Dasgupta and Lahiri (1993) show that business sentiments have explanatory power of forecasting business cycle turning points. Taylor and McNabb (2007) find that business confidence is procyclical and plays an important role in forecasting output downturns.

Although we focus on business confidence, our paper is related to a large body of previous re-

[1] Historically, the view that behavioural factors may influence investment decisions has been around at least since Keynes (1936) who famously invoked 'animal spirits' as an inducement to invest and noted: "*But individual initiative will only be adequate when reasonable calculation is supplemented and supported by animal spirits.*"(Chap 12, page 163).

[2] The appendix provides details on how the business confidence index is constructed.

search that has studied consumer confidence or sentiment and its ability to forecast macroeconomic variables. Leeper (1992) finds that consumer sentiment does not help predict industrial production and unemployment, especially when financial variables are taken into account. On the other hand, Matsusaka and Sbordone (1995) reject the hypothesis that consumer sentiment does not predict output. Carroll, Fuhrer and Wilcox (1994), Fuhrer (1993), Bram and Ludvigson (1998), Ludvigson (2004) and Cotsomitis and Kwan (2006) find that the consumer attitudes have some additional information about predicting household spending behaviour. Lahiri, Monokroussos and Zhao (2016) employ a large real-time dataset and find that the consumer confidence survey has important role in improving the accuracy of consumption forecasts. Christiansen, Eriksen and Møller (2014) find that consumer and business sentiments contain independent information for forecasting business cycles. Barsky and Sims (2012) find that consumer confidence reflects news about future fundamentals and a confidence shock has a persistent effect on the economy.

More recently, Angeletos, Collard and Dellas (2018) quantify the role of confidence for business cycle from both theoretical and empirical perspectives. They construct a measure of confidence within a Vector Autoregressive (VAR) framework by taking the linear combination of the VAR residuals that maximizes the sum of the volatilities of hours and investment at frequencies of 6 to 32 quarters. Their measure likely captures a mixture of consumer and business confidence and is, therefore, distinct from the survey-based measure that we use in our analysis.

We find that business confidence leads US business investment growth by one quarter. It leads structures investment, which is one of the major components of business investment, by two quarters. Our empirical analysis shows that investors' confidence has statistically significant predictive power for US business investment growth and its components (equipment and non-residential structures) after controlling for other determinants of investment. To better gauge the role of business confidence for investment growth, we also perform Out-Of-Sample (OOS) test for 1990Q1–2016Q4. Our findings suggest that the OOS test results are similar to the in-sample test results.[3]

While, as we found, business confidence has predictive power for total investment, it may also contain additional information on the trajectory of investment as captured by downturns and directional changes. This information would be of interest to policymakers in assessing the economy's near-term

[3] Rossi (2013) points out that it is not necessary for the in-sample results to be similar to OOS results.

outlook, over and above the general ability of business confidence to forecast investment. Indeed, we find that contemporaneous correlation between business confidence and investment growth rises during NBER recession dates. This property of the data suggests that it is worthwhile to explore the forecasting ability of business confidence for investment downturns and directional changes. Towards this end, we define investment downturns as business investment growth below the sample average for more than two consecutive quarters.[4] Using a static probit forecasting model, we assess the OOS forecasting ability of business confidence for investment downturns for 1990Q1–2016Q4. A key finding of this approach in the literature is that term spread and stock price contain information for forecasting US recessions (Estrella and Mishkin (1998); Nyberg (2010); Kauppi and Saikkonen (2008)). We follow a similar approach and find that business confidence has statistically significant forecasting power for investment downturns over 1–4 quarter forecast horizons in the US economy. It has stronger forecasting ability than the traditional predictors such as term spread, credit spread and stock price at 1–3 quarter forecast horizons. We also find strong evidence that the business confidence has good incremental predictive power for investment downturns over 1–4 quarter forecast horizons, controlling for other predictors of downturns.

Next, we evaluate the forecasting ability of business confidence for the direction of investment growth.[5] Using a static probit forecasting model, we find that business confidence has statistically significant OOS forecasting ability for direction of investment growth at 1–3 quarter forecast horizons. Remarkably, it exhibits superior forecasting performance for 2–quarter forecast horizon than other predictors, such as, stock price, term spread and credit spread. When we control for other predictors in the forecasting model, we find that business confidence has incremental forecasting power for the direction of investment growth for shorter forecast horizons.

Finally, we evaluate if the information in business confidence reflects either non-fundamental factors like 'animal spirits' or news about future fundamentals. We follow a VAR model approach similar to Barsky and Sims (2012) for consumer confidence, and evaluate the dynamic behaviour of different components of investment growth to a surprise increase in investor's confidence. A positive business

[4]This definition is similar to that in Taylor and McNabb (2007) for output downturns.

[5]Many previous studies have focused on sign of stock market returns (see Christoffersen and Diebold (2006), Christoffersen, Diebold, Mariano, Tay and Tse (2007) and Nyberg (2011)). Christoffersen and Diebold (2006) find a link between asset return volatility and asset return sign predictability.

confidence shock increases US business investment growth on impact, followed by a hump-shaped response for shorter (5-6 quarter) horizons. This response is also statistically significant. This finding suggests that business confidence innovations clearly convey important information about the future paths of investment growth, most notably at shorter horizons. Since the effects dissipate within about two years, it is likely that the information in business confidence reflects primarily non-fundamental factors. This conclusion follows the interpretation in Barsky and Sims (2012). Interestingly, they find that effects of consumer confidence shocks on non-durable consumption are persistent and capture changes in expected productivity (future fundamentals). By contrast, we find that the effects of business confidence shocks on investment are relatively transient and likely reflect short-lived 'animal spirits'.

The rest of the paper is organized in 6 sections. In section 2, we describe the data and preliminaries. In section 3, we determine the incremental predictive ability of business confidence for investment growth and its components, using in-sample and OOS data. In section 4, we evaluate the OOS forecasting ability of business confidence for investment downturns and direction of investment growth, using a probit forecasting model. In section 5, we examine the impulse responses of business investment growth to business confidence innovations. In section 6, we present a variety of robustness checks and section 7 concludes.

2 Data and preliminaries

Our quarterly data span the period 1955Q1–2016Q4. We obtain the business confidence index from the leading indicator database of the OECD. We use quarterly data for real gross domestic product, business investment and cash flow from the Bureau of Economic Analysis (BEA). We collect data for term spread, credit spread, and the prime business rate of commercial banks from the Board of Governors of the Federal Reserve System, and the data for stock price from Yahoo! Finance.[6] To be consistent with the timing of the survey, we convert monthly data to quarterly frequency of business confidence indices and other variables (e.g. stock price, prime business rate of commercial banks), by taking the value of the third month of each quarter (e.g. March, June, September and December). Figure 1 shows the main data used in the analysis and Table 1 describes the abbreviation of the list of

[6]The Appendix provides the details of data construction and sources.

all the variables.

Table 1: List of variables

BCI	Business confidence index
TS	Term spread
CS	Credit spread
TBI	Log of real total business fixed investment
SI	Log of real non-residential structure investment
EI	Log of real equipment investment
IPI	Log of real intellectual property product investment
GDP	Log of real gross domestic product
CC	Log of user cost of capital
SP	Log of real stock market price
CF	Log of real cash flow

As a preliminary check, we begin by examining the stationarity properties of the data to motivate the empirical specifications.[7] We first conduct the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests. We choose the number of lags of the explanatory variables based on the Akaike Information Criterion (AIC) for each variable in the ADF tests and set the maximum lag length of variables to four. The number of lags for the PP test is four. The ADF and PP tests reject the null hypothesis of unit root for BCI, TS and CS in levels at the 1% significance level. Except for these variables, the ADF and PP tests fail to reject unit roots in log-levels at the 1% level of significance. These variables are, however, stationary in first-difference of log-levels. Hence, our specifications are in growth rates.

Next, we examine the cross-correlations between BCI at time (t) and ΔTBI (and its components) at time $(t+j)$. The largest correlation is 0.66 between BCI at time (t) and ΔTBI at time $(t+1)$. This pattern implies that BCI leads ΔTBI by one quarter. The cross-correlations between BCI and ΔSI show that BCI leads ΔSI by two quarters. The cross-correlations of BCI with ΔEI and ΔIPI, respectively, show that the contemporaneous correlations in both cases are the largest, thus, there are no lead and lag patterns.

[7] To save space, we have put all the associated Tables and Figures from this section in the appendix.

We examine the direction of causality between BCI and ΔTBI (and its components) based on bi-variate VAR model. We find clear evidence for a unidirectional Granger-causality of BCI to ΔTBI, and its components, ΔSI, ΔEI and ΔIPI. We also perform Granger-causality test using multivariate VAR model. We include six variabes, namely, ΔTBI (or its components), ΔSP, ΔCC, ΔCF, ΔGDP and BCI. There is evidence of a unidirectional Granger-causality of BCI to ΔTBI and its two major components, ΔSI and ΔEI. The Granger-causality tests suggest that BCI is informative in predicting US investment growth. We now turn to investigating this in more detail.

3 Does business confidence predict investment growth?

In this section, we use the Autoregressive Distributed Lag (ARDL) model to assess whether BCI helps explain investment growth after controlling for other economic variables that are traditionally considered in empirical investment specifications. We use in-sample and OOS tests in our empirical analysis.

3.1 ARDL Model

In order to specify the ARDL model for business investment growth that does not include BCI, we follow Barro (1990) and Rapach and Wohar (2007) and consider the following baseline specification:

$$\Delta \log I_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \Delta \log I_{t-i} + \sum_{i=1}^{q} \gamma_i Z_{t-i} + \upsilon_t, \tag{1}$$

where the dependent variable, $\Delta \log I_t$, denotes ΔTBI and its components, namely, ΔSI, ΔEI, and ΔIPI. We estimate four different models for each category of business investment. We use υ_t and q to denote the error term and number of lags of the variables, respectively. We use Z_{t-i} to denote a vector of control variables, which includes ΔSP, ΔCC, ΔCF and ΔGDP. These variables are commonly used in the previous literature. Following Jorgenson (1963), we choose output and user cost of capital since the neoclassical investment model suggests that investment depends on the change in output and the change in the user cost of capital. We also include cash flow and stock market prices as control variables in the model as a large body of previous empirical work has shown their relevance in predicting future investment opportunities (see Gilchrist and Himmelberg (1995)).[8] Barro (1990) uses real stock price

[8] Chirinko and Schaller (2001) also use neoclassical model where dependent variable is investment rate and the regressors are the level and lag of change in output, the level and lag of change in the cost of capital and

as an regressor and suggests that it is potentially a better measure than the average Tobin's Q in predicting investment growth.

To judge the predictive power of BCI for investment growth, we add BCI to the baseline model in (1) to get a BCI-nested model as:

$$\Delta \log I_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \Delta \log I_{t-i} + \sum_{i=1}^{q} \gamma_i Z_{t-i} + \sum_{i=1}^{q} \beta_i BCI_{t-i} + \upsilon_t, \tag{2}$$

We employ two types of statistical tests to investigate whether BCI has any predictive ability after controlling for other relevant economic variables mentioned above.[9]

3.1.1 In-sample results

For the in-sample test, we evaluate the increment in adjusted R^2 (denoted as $\bar{R}^2$), provided by the regressions of the various measures of business investment growth on lag values of BCI including control variables over the period 1955Q1–2016Q4. Next, we conduct hypothesis tests using a heteroskedasticity and autocorrelation robust covariance matrix computed with Newey-West estimator with four lags. The null hypothesis of zero coefficients, $\beta_i = 0\,(i = 1, ..., q)$, is rejected if the corresponding p-value falls below the desired level of significance.

Table 2 reports the estimation results from baseline model (1) and BCI-nested model (2) to assess the predictive ability of BCI for ΔTBI and its components. We use the AIC to determine the number of lags in each regression. To estimate ΔTBI and ΔEI, we use two lags. We use three lags and four lags to estimate ΔSI and ΔIPI, respectively.

Panel (a) reports $\bar{R}^2$ and p-values of the joint significance of all the coefficients—not including the intercept from the baseline model. The model variables explain 45.9% of the variation in the next quarter's ΔTBI. Similarly, these variables explain 46%, 38.3% and 28.7% of the variation in ΔIPI, ΔEI and ΔSI, respectively. Next, we perform the joint null hypothesis of zero coefficients of all explanatory variables excluding the intercept and reject the null since the corresponding p-value is 0.000 for each specification.

liquidity, where liquidity is retained earnings plus depreciation.

[9] Allowing for different lags for different sets of variables in (2) does not affect our empirical findings (the results are available upon request).

Panel (b) reports the incremental $\bar{R}^2$ (the $\bar{R}^2$ from BCI-nested model minus the $\bar{R}^2$ from the baseline model) and the p-values of the joint significance of all lags of BCI from the BCI-nested model. We find that BCI has strong predictive ability for ΔTBI in the US economy. The incremental $\bar{R}^2$ is 6.7%, which means that BCI has 6.7% additional explanatory power of the variation for ΔTBI after controlling for other determinants of investment. The joint null hypothesis that the lags of BCI do not have predictive power for ΔTBI is rejected at the 1% level of significance since the p-value is 0.000. We also evaluate the incremental predictive power of BCI for the components of the business investments. We find that the BCI has strong predictive ability for ΔEI with the incremental $\bar{R}^2$, 7.5% and the coefficients of BCI are jointly statistically significant. BCI has some predictive power for ΔSI. We reject the null hypothesis that lags of BCI do not help predict ΔSI at 5% significance level. For ΔIPI, however, the incremental $\bar{R}^2$ is quite low and the coefficients of lagged values of BCI are jointly insignificant at the 10% level. Overall, BCI has unique information in predicting US investment growth.

3.1.2 OOS results

We now turn to the OOS predictive performance of BCI for ΔTBI and its components over the 1990Q1–2016Q4 period. We employ the recursive estimation of equations (1) and (2), adding one quarter at a time to obtain a series of one-step-ahead forecasts.[10] The recursive estimation is more efficient and performs better than rolling window estimation in point forecasting (see Carriero et al. (2015)).[11] To evaluate the one-step-ahead predictability of BCI for business investment growth, we compute the OOS R^2 (R^2_{OS}), which is calculated as follows:

$$R^2_{OS} = 1 - (MSFE_i/MSFE_j), \tag{3}$$

where MSFE is the Mean Squared Forecast Error corresponding to the forecast and is defined as:

$$MSFE = P^{-1} \sum_{t=R+1}^{T} \left(\Delta \log (I_t) - \Delta \widehat{\log (I_t)} \right)^2 \tag{4}$$

where T denotes the total number of sample observations, while R and P denote in-sample and OOS observations, respectively. $MSFE_i$ and $MSFE_j$ are from equations (2) and (1), respectively. A positive

[10] The general set up for obtaining OOS data is similar to Estrella and Mishkin (1998).

[11] The results for the rolling window estimation are available upon request. Notably, the recursive estimation scheme performs better for structures investment, and with statistical significance, relative to the rolling-window estimation.

R^2_{OS} indicates that BCI has OOS predictive power for investment growth after controlling for other determinants. We use Clark and West (2007) statistic corresponding to a test of the null hypothesis that $MSFE_i \geq MSFE_j$ against $MSFE_i < MSFE_j$ which is equivalent to the null hypothesis of $R^2_{OS} \leq 0$ against $R^2_{OS} > 0$.

Table 3 includes the results of OOS predictive performance of BCI for ΔTBI and its components. It reports the R^2_{OS} and p-value for the Clark and West (2007) statistics. The R^2_{OS} captures the improvement in MSFE from the BCI-nested model relative to MSFE from the baseline model. Since the R^2_{OS} for ΔTBI is 0.052, BCI has OOS predictive ability for future ΔTBI after controlling for other determinants of investment. The null hypothesis of $R^2_{OS} \leq 0$ against $R^2_{OS} > 0$ is rejected at the 1% level since the p-value is 0.006. The R^2_{OS} values are 0.033 and 0.016 for ΔSI and ΔEI, respectively, and are statistically significant at the 5% level. These values imply that BCI has incremental OOS predictive power for future ΔSI and ΔEI after using the control variables. For ΔIPI, however, we find that the R^2_{OS} value is close to zero, which implies that BCI does not have incremental predictive ability for this component of business investment.

We next use a visual device proposed by Goyal and Welch (2003, 2008). Specifically, a graph of Cumulative Difference in Squared Forecast Errors (CDSFE) to assess the OOS predictive ability of BCI for investment growth after controlling variables. The CDSFE is cumulative squared forecast errors from baseline model minus cumulative squared forecast errors from BCI-nested model. We calculate the CDSFE as follows:[12]

$$CDSFE_{R+1:T} = \sum_{s=R+1}^{T} \left(\hat{u}^2_{j,s} - \hat{u}^2_{i,s} \right)$$

where, $\hat{u}^2_j$ and $\hat{u}^2_i$ are squared forecast errors from the baseline model and BCI-nested model, respectively. We denote in-sample and full observations as R and T, respectively. Figure 2 displays the relative performance of the baseline model to the BCI-nested model. A positive value shows that the BCI-nested model outperforms the baseline model. Panel (a) shows that BCI exhibits OOS predictability for ΔTBI all the time of OOS forecasting period. In particular, the forecasting performance of the BCI-nested model improves during the NBER recession dates. Additional, the OOS predictive ability increases in the period following the financial crisis of 2008. Panels (b–d) show the forecasting

[12] Goyal and Welch (2003, 2008) use this approach to show the CDSFE of historical average vs. predictive variable's regression.

performance for the components of ΔTBI. BCI-nested model of ΔSI outperforms the baseline model over the OOS period and it improves forecasting performance significantly during the financial crisis and after 2011. For ΔEI, BCI has OOS predictability in 1991–1993, 1995–1996 and 2013–2016 and substantially improved during the financial crisis of 2008. Finally, the figure shows that BCI never outperforms to predict ΔIPI. Overall the BCI-included investment forecasting model exhibits the OOS predictability for ΔTBI and its components (except ΔIPI), more importantly during the financial crisis and the period afterwards.

4 Does BCI forecast investment downturns and direction of investment?

Having established that BCI helps predict quarterly business investment growth, we now investigate its forecasting ability for business investment downturns as well as the direction of business investment growth. In this analysis, we treat both as discrete events.

4.1 Investment downturns

Does BCI have information about future investment downturns? If the answer is affirmative then policy makers can take this information into account and be better prepared for dealing with the consequences of such downturns from spreading to the broader economy. We define the business investment downturns indicator, $d_t, t = 1, 2, ..., T$ as a binary-valued stochastic process that only takes on values 0 and 1 depending on the state of the economy. These two values are characterized as follows:[13]

$$d_t = \begin{cases} 1, & \text{if the business investment growth is below the sample average for more than} \\ & \text{two consecutive quarters.} \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

The sample average of total US business investment growth is 1.07% for the period 1955Q1–2016Q4. We plot BCI against investment downturns in Figure 3. Interestingly, there is evidence of all downturns are preceded by a fall in BCI and all major falls in BCI are followed by a downturn, except in 1980.

[13]This definition is similar to that used for output downturns in Taylor and McNabb (2007).

We consider a static probit forecasting model to evaluate the forecasting power of BCI for business investment downturns and use the maximum likelihood method to estimate the model.[14] Let Ω_t be the information set available at time t. Conditional on Ω_{t-1}, d_t has a Bernoulli distribution, $B(.)$, with probability with p_t. The conditional probability of investment downturns, d_t=1, satisfies:

$$p_t = E_{t-1}(d_t) = P_{t-1}(d_t = 1) = \Phi(\pi_t), \tag{6}$$

where $E_{t-1}(.)$ and $P_{t-1}(.)$ represent the conditional expectation and probability given the information set, Ω_{t-1}, respectively. We denote the standard normal cumulative distribution function as Φ. First, we examine the forecasting ability of each forecasting variable for investment downturns using a univariate probit model:

$$\pi_t = \omega + \psi X_{t-k}, \tag{7}$$

where X_{t-k} represents predictive variables and k denotes the forecast horizon. We consider 1–4 quarter forecast horizons and use ΔGDP, ΔSP, ΔCF, ΔCC, TS, CS and BCI as predictive variables. The previous literature has established that the variables, ΔGDP, ΔCF, ΔSP and ΔCC, are the conventional predictors and TS, ΔSP, and CS are good predictors of recessions. In particular, TS and ΔSP help forecast US recessions (see Estrella and Mishkin (1998); Kauppi and Saikkonen (2008); Nyberg (2010)). Gilchrist and Zakrajšek (2012) evaluate the relationship between credit spread and real economic activity and find that CS has good predictive power for US business cycle fluctuations. Ponka (2017b) shows that CS has significant predictive power for US recessions.

Second, we evaluate the predictive power of the BCI for investment downturns after controlling for other relevant variables, namely, TS, CS and ΔSP.

$$\pi_t = \omega + \delta V_{t-k} + \phi BCI_{t-k}, \tag{8}$$

where, V_t denotes the vector of control variables.

[14]Previously, the probit model has been used by Estrella and Mishkin (1998), Kauppi and Saikkonen (2008), Nyberg (2010), Christiansen et al. (2014), Chen, Chou and Yen (2016), among others, to forecast recessions. The main difference relative to these papers and other previous research is that our focus is on investment downturns, not output recessions.

4.1.1 Results

We employ OOS test for the period 1990Q1–2016Q4. Pönkä (2017a) finds that the more parsimonious static probit model performs better than the dynamic probit model for the OOS test even though the dynamic extensions of the probit model yield the best fit for the in-sample test.[15] We use recursive estimation, adding one quarter at a time to obtain a series of k-step-ahead forecasts for the period 1990Q1–2016Q4.[16] We use three forecast evaluation methods. First, we use pseudo R^2, denoted as ps.R^2, developed by Estrella (1998).[17] It is defined as:

$$\text{ps.}\, R^2 = 1 - (\log L_u / \log L_c)^{-(2/n)\log L_c}, \tag{9}$$

where L_u represents the value of the maximized probit likelihood, and L_c denotes the value of the maximized likelihood under the constraint that all coefficients are zero, except for the constant. The value of ps.R^2 is between 0 and 1 that corresponds to 'no fit' and 'perfect fit', respectively, and has the same interpretation as the coefficient of determination in the usual linear case. Second, we use the Quadratic Probability Score (QPS) proposed by Diebold and Rudebusch (1989). The QPS is calculated as follows:

$$QPS = P^{-1} \sum_{t=R+1}^{T} 2\left(\hat{P}(d_{t+h} = 1) - d_{t+h}\right)^2, \tag{10}$$

where T denotes the total number of sample observations, while R and P denote in-sample and OOS observations, respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy.

Finally, following Berge and Jordà (2011) who have introduced Receiver Operating Characteristics (ROC) curves to applications in economics, we consider this approach for forecast evaluation. The ROCs are not tied to a specific loss function and evaluate the model's classification ability to distinguish between investment downturns and expansions. The ROC curve plots all possible combinations of true positive rates and false positive rates using various possible threshold values from 0 to 1.[18] The 45°

[15] We consider dynamic probit model in the robustness section.

[16] The results based on the alternative approach of rolling-window estimation are available upon request.

[17] In probit models, the ps.R^2 of Estrella (1998) is used by Estrella and Mishkin (1998), Kauppi and Saikkonen (2008), Nyberg (2010), Christiansen et al. (2014) and Chen et al. (2016), among others, in order to evaluate model fit.

[18] Berge and Jordà (2011) and Liu and Moench (2016) provide a detailed discussion of the ROC curves, where they use them to assess the classification abilities of various leading indicators into recessions and expansions.

diagonal running from bottom-left to top-right corner represents a random guess classifier. If the ROC curve touches the top-left corner it implies that the model has perfect classifier. We test the null hypothesis of no classification ability ($H_0 : AUC = 0.5$) using a standard method of Hanley and McNeil (1982). We report the area under the ROC curve (AUC) that measures the overall performance of model's classification ability. The AUC is calculated as:

$$AUC = \int_0^1 ROC(r)dr, \tag{11}$$

where r is the false positive rate. A higher AUC value implies a better forecasting performance.

Table 4 displays the value of ps.R^2, QPS and AUC from OOS results for each predictor from equation (7). Even though there are chances of a negative ps.R^2, we do not find any negative ps.R^2. The BCI has OOS predictive ability for all forecast horizons between 1 and 4 quarters. The null hypothesis of no classification ability of BCI is rejected for all forecast horizons. BCI performs the best as a predictor in the case of the 1–quarter forecast horizon, compared to other forecast horizons. The ps.R^2 for BCI is 27.7%, which implies that the BCI explains 27.7% OOS variation in investment downturns. The value of QPS is 0.343, which is the lowest and the value of AUC is 0.790, which is the highest for the 1–quarter forecast horizon. The values of ps.R^2, QPS and AUC for 2–3 quarter forecast horizons are quite close to the value for the 1–quarter forecast horizon. However, the ps.R^2 for BCI is 9.9% is somewhat lower in the 4–quarter horizon relative to other forecast horizons.

In Figure 4, panels (a)-(d) display the ROC curves for BCI, TS and ΔSP for 1–4 quarter forecast horizons, respectively. The BCI is more accurate in classifying investment downturns than TS and ΔSP over 1–3 quarter forecast horizons. In Figure 5, panels (a)-(d) display the OOS investment downturns probability forecasts for BCI, TS and ΔSP for 1–4 quarter forecast horizons, respectively. The downturn dates are indicated by grey lines. The BCI gives stronger signals than other variables about the downturns period for the 1–3 quarters forecast horizons. This finding is consistent with the information in Table 4 and Figure 4. Overall, based on the results, BCI exhibits superior OOS predictive performance for investment downturns over the 1-3 quarters forecast horizons relative to other predictors.

The other two predictors, ΔSP and ΔGDP, exhibit statistically significant OOS predictive ability for all forecast horizons. The popular predictor of output downturns, TS, has statistically significant

OOS predictive ability for a 4–quarter forecast horizon. CS and ΔCC have predictive ability for 1–2 quarter forecast horizons. However, ΔCF does not have OOS predictive ability for all forecast horizons.

We next consider a model with control variables such as TS, CS and ΔSP to evaluate the independent forecasting power of BCI for business investment turning points. We estimate the probit model in (8) without BCI and with BCI. Table 5 reports the results. The BCI-nested model exhibits better statistically significant OOS predictive performance relative to the BCI non-nested model for all forecast horizons. Figure 6 displays the OOS investment downturns probability forecast, using TS, CS and ΔSP as control variables and confirms the message from the table. Overall, these results suggest that BCI has independent forecasting ability for investment downturns. However, the evidence is relatively strong for downturns in total investment and structures prior to 2005. One potential reason may be that we observe relatively more variation in the relationship between business confidence and total investment since 2005 as evident from Figure 1 (panel F).

4.2 Directional forecasts of investment growth

We next extend our analysis by predicting the direction of investment growth. Previous research using directional forecasting includes Christoffersen and Diebold (2006) and Christoffersen, Diebold, Mariano, Tay and Tse (2007) who demonstrate a theoretical link between asset return volatility and asset return sign forecastability. Nyberg (2011) uses dependent dynamic probit model in predicting the direction of excess stock returns and finds that the returns sign is predictable in-sample when combined with recession forecasts. Our focus is to explore whether BCI plays a role in predicting the sign of investment growth, which is different from these previous studies.

Let g_t be a series of direction of business investment growth and ζ_t be the information set available at time t. We define g_t is 1 if the sign of investment growth is positive and 0, otherwise. Conditional on ζ_{t-1}, g_t has a Bernoulli distribution B(.) with probability with p_t. The conditional probability of a positive sign of investment growth, $g_t|\zeta_{t-1} = 1$, satisfies:

$$p_t = E_{t-1}(g_t|\zeta_{t-1}) = P_{t-1}(g_t|\zeta_{t-1} = 1) = P_{t-1}(g_t > 0|\zeta_{t-1}) = \Phi(\Pi_t), \tag{12}$$

where $E_{t-1}(.)$ and $P_{t-1}(.)$ represent the conditional expectation and probability on the given information set, ζ_{t-1}, respectively. We use Φ to denote the standard normal cumulative distribution function.

As before, we use a static univariate probit model and same predictors to examine the forecasting performance for direction of investment growth:

$$\Pi_t = \varphi + \kappa X_{t-k}. \tag{13}$$

We then evaluate whether BCI improves the directional forecasts for investment growth using control variables.

$$\Pi_t = \varphi + \theta C_{t-k} + \vartheta BCI_{t-k}, \tag{14}$$

where, C_t refers to a vector of control variables. We again use the traditional predictors, TS, CS and ΔSP as control variables. We examine the OOS predictive performance over the period 1990Q1–2016Q4 and employ the forecasting measures, namely, ps.R^2, QPS and AUC to evaluate the directional forecasts as before in forecasting investment downturns. We also calculate the Success Ratio (SR), which is simply the percentage of correct forecast as it commonly used to evaluate the directional forecasting performance (see Nyberg (2011) and Pönkä (2017a)). We use a common and natural threshold, $c = 0.5$, for sign forecasts, $\hat{g}_t = \mathbf{1}[p_t > c]$.

We use the Pesaran and Timmermann (2009) test statistics, denoted as PT to evaluate the directional accuracy. The PT test is also suitable for market timing when there is serial correlation in the realized value, g_t, and the sign forecasts, $\hat{g}_t$. The null hypothesis is that the value of SR does not differ from the ratio that would be obtained in the case of no predictability, when g_t and $\hat{g}_t$ are independent. Table 6 reports the values of ps.R^2, QPS, AUC and SR for each predictor from (13). BCI has OOS predictability for direction of investment growth for 1–3 quarter forecast horizons. The values of AUC and SR are statistically significant for 1–3 quarter forecast horizons. The values of ps.R^2, QPS, AUC and SR for the BCI are 23.1%, 0.299, 0.768 and 0.833 for 1–quarter forecast horizon, respectively.

For the 2–quarter forecast horizon, the values of ps.R^2, AUC and SR for the BCI are 24.7%, 0.775, 0.796, which are the highest, respectively. The value of QPS is 0.312, which is the lowest. These findings imply that BCI has superior OOS predictability for direction of investment growth in 2–quarter forecast horizon relative to other predictors. For 3–quarter forecast horizon, the values of ps.R^2, QPS, AUC and SR are close to their respective values for 2–quarter forecast horizon. The BCI has no OOS predictability for direction of investment growth for 4–quarter forecast horizon.

The predictor, ΔGDP, has OOS predictive ability for 1 and 3 quarters forecast horizons, whereas, CS

and ΔSP exhibit statistically significant OOS predictive ability only for 3–4 quarter forecast horizons, respectively. However, TS and ΔCF exhibit no directional predictability for all forecast horizons. Finally, we evaluate the predictive power of BCI for direction of investment growth, using control variables such as TS, CS and ΔSP. We estimate the model (14) without BCI and with BCI, respectively. Table 7 reports the results. The BCI-nested model has better OOS predictive performance relative to BCI non-nested model over 1–3 quarter forecast horizons.

5 Business confidence shock

We now turn to a simple multivariate VAR model to assess the impulse responses of investment growth and its components to a positive exogenous shock in BCI. Specifically, we estimate the following six-variables VAR model (dropping the constant term for notational convenience):

$$Y_t = \sum_{i=1}^{N} A_i Y_{t-i} + \nu_t, \tag{15}$$

where, $Y_t = [BCI_t, Z_t, \Delta \log (I_t)]'$ and $\nu_t = [\nu_{1t}, \nu_{2t}, \nu_{3t}, \nu_{4t}, \nu_{5t}, \nu_{6t}]'$ is a vector of orthogonalized shocks. We use ν_{1t} and Z_t to denote the BCI shock and a vector of ΔSP, ΔCC, ΔCF, ΔGDP variables, repectively. The investment growth, $\Delta \log I$ represents ΔTBI, ΔSI, ΔEI, and ΔIPI for four different VAR models. We use AIC to determine lags and use 2 lags to estimate ΔTBI, ΔSI and ΔEI. To estimate ΔIPI, we use 4 lags.

We employ the standard Cholesky orthogonalization and order BCI first followed by ΔSP, ΔCC, ΔCF, ΔGDP and $\Delta \log I$. This ordering assumes that the business confidence is fully exogenous and does not reflect information contained in other variables in the VAR. We consider the opposite informational assumption below. Figure 7 shows the impulse responses of investment growth and its components to an unexpected one standard deviation positive shock to BCI. The shaded areas are bootstrap confidence bands at the 95% significance level. Panel (a) shows the impulse responses of ΔTBI. A positive exogenous shock to BCI has positive impact effect on ΔTBI and statistically significant. The impulse responses appear statistically significant for four-quarters ahead. We graphically depict the impulse responses of ΔSI, ΔEI and ΔIPI in panels (b)–(d). An innovation in BCI has a statistically significant positive impact effect on ΔEI and ΔIPI. More interestingly, the maximum impulse response of ΔEI is more than 1% and statistically significant. We find evidence that ΔSI actually falls

slightly on impact before rising after a BCI shock. The impulse responses are statistically significant for 6-quarters ahead and insignificant for future periods. The impulse responses of all measures of investment growth are hump-shaped and short-lived. BCI innovations, thus, clearly convey important information about the future paths of investment growth, most notably at shorter horizons.

Now we consider an alternative ordering whereby innovation in business confidence reflects information already contained in the innovations of all the other variables in the VAR. Specifically, we reorder the variables but now BCI is ordered last in the VAR system such that BCI is orthogonalized with respect to other determinants of investment (ΔSP, ΔCC, ΔCF and ΔGDP). Figure 8 shows the responses of investment growth and its component to a BCI shock. There is no qualitative difference in the impulse responses of ΔTBI, ΔEI and ΔSI. So, BCI innovation predicts ΔTBI and its important components, ΔSI and ΔEI, under both orthogonalizations. However, ΔIPI has a muted response to the BCI shocks and the response is almost never statistically significant under this orthogonalization. Following Barsky and Sims (2012), we interpret the short-lived impulse responses to a business confidence shock as reflecting non-fundamental 'animal spirits'-type information in business confidence.

6 Robustness checks

In this section we present a variety of checks to establish the robustness of our findings. First, we include expected growth and interest rate as additional controlling variables to estimate the investment growth and its components. Second, we show how our approach of converting monthly to quarterly frequency is robust to alternative assumptions. Third, we use alternative dates of investment downturns to assess the predictive ability of BCI for investment downturns as in section 4.1. Fourth, we use a dynamic forecasting probit model and show that our results from static model are robust. Finally, we show that our finding–BCI innovations have a statistically significant short-term effect on investment—is robust to alternative ordering of the variables (hence alternative informational structures) in the VAR.

6.1 Expected growth, interest rate and BCI

We include expected output growth and interest rates as additional explanatory variables in equation 1 and 2 and perform in-sample and OOS tests. We construct a predicted value of output growth based on a regression of output growth on its four lags. Table 8 and Table 9 show the results. Our findings

are consistent with previous in-sample and OOS performance results without expected growth and interest rate.

6.2 Different approaches to use monthly data for quarterly estimation

We make different assumptions for converting monthly to quarterly data instead of using third month of the quarter for BCI and estimate the ARDL model. First, we use BCI quarterly data by taking average of three months. Second, we use first month of the quarter to convert quarterly data and finally, use weighted average of 0.1, 0.3 and 0.6 of first, second and third month, respectively. Table 11 shows the results. Panel (a) of the table shows the baseline results. Panel (b–d) show the results from the first, second and third approaches, respectively. The incremental $\bar{R}^2$ from using third month of the quarter for BCI in Table 2 (our baseline) is higher than from other approaches of converting monthly to quarterly frequency in Table 11.

6.3 Alternative downturn dates

We use a set of alternative investment downturn dates to evaluate the robustness of forecasting performance of BCI for the investment downturns. According to the alternative definition, we define an investment downturn is 1 if the total investment growth is negative for more than two consecutive quarters and zero, otherwise. The overall set up of the estimation is similar to the section 4. We then estimate equation (7) to evaluate the forecasting performance. Table 10 shows the values of ps.R^2, QPS and AUC from the OOS results. The values of ps.R^2 are 41.7%, 45.9%, 31.2% and 8.2% for 1–4 quarter forecast horizons, respectively. The values of AUC are 0.890, 0.909, 0.899 and 0.796, which are close to 1, for 1–4 quarter forecast horizons, respectively, and are statistically significant. These results imply that BCI has statistically significant OOS predictability for investment downturns for 1–4 quarter forecast horizons and the results are almost similar to those results from our baseline definition of investment downturns.

6.4 Dynamic probit model

We consider an extension to the static model by adding a lagged value of the dependent variable to evaluate the robust BCI's forecasting performance for the investment downturns.[19] We make assumptions on what information available at the time of forecast and use three quarter information lags of dependent variable.[20] The dynamic probit model is:

$$\pi_t = \omega + \zeta d_{t-k-3} + \delta V_{t-k} + \phi BCI_{t-k}, \tag{16}$$

where V_t is a vector of controlling variables. We choose three controlling predictors, TS, CS and ΔSP as before in static model and estimate the dynamic probit model (16) without BCI and with BCI. Table 12 reports the results. The BCI-nested model exhibits better statistically significant OOS predictive performance relative to the BCI non-nested model for all forecast horizons and confirms that BCI has robust forecasting performance for investment downturns even in the dynamic forecasting model.

6.5 Ordering free VAR

We now assess the impulse responses of ΔTBI to one standard deviation BCI shocks, using random ordering of six-variables in VAR structure. Figure 9 shows the results. Any specification of ordering, the impulse responses of ΔTBI to BCI innovations are hump-shaped, short-lived and statistically significant. This exercise conforms that our results are robust that BCI innovations has important information about the future business investment.

7 Conclusion

Despite the popularity of business confidence as a leading indicator of future output, the direct link between the former and business investment has not yet been investigated. Our paper fills this gap in the literature. Using quarterly US data for over sixty years, we investigate whether confidence

[19] Kauppi and Saikkonen (2008), Nyberg (2010), Pönkä (2017a) and among others show dynamic probit model increases the forecasting performances.

[20] Nyberg (2010) uses nine months lags of the dependent variable (recession indicator) due to the NBER announcement delay.

predicts business investment, and whether confidence can forecast investment downturns and the direction of investment growth. We find that business confidence leads US business investment growth by one quarter, and structures by two quarters; and business confidence has predictive ability for investment growth even after controlling for conventional factors such as output, user costs, cash flows, and stock prices. Business confidence has a superior predictive power, relative to traditional factors, for investment downturns over 1–3 quarter forecast horizons and direction of investment growth over 2–quarter forecast horizons in the US economy. Impulse response analysis reveals that exogenous shifts in business confidence reflect short-lived non-fundamental factors, consistent with the 'animal spirits' view of investment. Our findings have implications for improving investment forecasts, developing new business cycle models, and studying the role of behavioural factors determining investment growth.

References

Ang, J. B.: 2010, Determinants of private investment in Malaysia: What causes the post-crisis slumps?, *Contemporary Economic Policy* **28**, 378–391.

Angeletos, G.-M., Collard, F. and Dellas, H.: 2018, Quantifying confidence, *Econometrica* **86**(5), 1689–1726.

Barro, R. J.: 1990, The stock market and investment, *Review of Financial Studies* **3**, 115–131.

Barsky, R. B. and Sims, E. R.: 2012, Information, animal spirits, and the meaning of innovations in consumer confidence, *American Economic Review* **102**, 1343–1377.

Berge, T. J. and Jordà, Ò.: 2011, Evaluating the classification of economic activity into recessions and expansions, *American Economic Journal: Macroeconomics* **3**, 246–277.

Bram, J. and Ludvigson, S. C.: 1998, Does consumer confidence forecast household expenditure? A sentiment index horse race, *Economic Policy Review, Federal Reserve Bank of New York, June* pp. 59–78.

Carriero, A., Clark, T. E. and Marcellino, M.: 2015, Bayesian VARs: Specification choices and forecast accuracy, *Journal of Applied Econometrics* **30**, 46–73.

Carroll, C. D., Fuhrer, J. C. and Wilcox, D. W.: 1994, Does consumer sentiment forecast household spending? If so, why?, *American Economic Review* **84**, 1397–1408.

Chen, S.-S., Chou, Y.-H. and Yen, C.-Y.: 2016, Predicting US recessions with stock market illiquidity, *B.E. Journal of Macroeconomics (Contributions)* **16**, 93–123.

Chirinko, R. S. and Schaller, H.: 2001, Business fixed investment and "bubbles": The Japanese case, *American Economic Review* **91**, 663–680.

Christiansen, C., Eriksen, J. N. and Møller, S. V.: 2014, Forecasting US recessions: The role of sentiment, *Journal of Banking and Finance* **49**, 459–468.

Christoffersen, P. F. and Diebold, F. X.: 2006, Financial asset returns, direction-of-change forecasting, and volatility dynamics, *Management Science* **52**, 1273–1287.

Christoffersen, P. F., Diebold, F. X., Mariano, R. S., Tay, A. S. and Tse, Y. K.: 2007, Direction-of-change forecasts based on conditional variance, skewness and kurtosis dynamics: International evidence, *Journal of Financial Forecasting* **1**, 1–22.

Clark, T. E. and West, K. D.: 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* **138**, 291–311.

Cotsomitis, J. A. and Kwan, A. C.: 2006, The usefulness of consumer confidence in forecasting household spending in Canada: A national and regional analysis, *Economic Inquiry* **44**, 185–197.

Dasgupta, S. and Lahiri, K.: 1993, On the use of dispersion measures from NAPM surveys in business cycle forecasting, *Journal of Forecasting* **12**, 239–253.

Diebold, F. X. and Rudebusch, G. D.: 1989, Scoring the leading indicators, *Journal of Business* **62**, 369–391.

Estrella, A.: 1998, A new measure of fit for equations with dichotomous dependent variables, *Journal of Business & Economic Statistics* **66**, 198–205.

Estrella, A. and Mishkin, F. S.: 1998, Predicting US recessions: Financial variable as leading indicators, *Review of Economics and Statistics* **80**, 45–61.

Fuhrer, J. C.: 1993, What role does consumer sentiment play in the US macroeconomy?, *New England Economic Review* pp. 32–44.

Gilchrist, S. and Himmelberg, C. P.: 1995, Evidence on the role of cash flow for investment, *Journal of Monetary Economics* **36**, 541–572.

Gilchrist, S. and Zakrajšek, E.: 2012, Credit spreads and business cycle fluctuations, *American Economic Review* **102**, 1692–1720.

Goyal, A. and Welch, I.: 2003, Predicting the equity premium with dividend ratios, *Management Science* **49**, 639–654.

Goyal, A. and Welch, I.: 2008, A comprehensive look at the empirical performance of equity premium prediction, *The Review of Financial Studies* pp. 1455–1508.

Hall, R. E. and Jorgenson, D. W.: 1969, Tax policy and investment behavior: Reply and further results, *American Economic Review* **59**, 388–401.

Hanley, J. A. and McNeil, B. J.: 1982, The meaning and use of the area under a Receiver Operating Characteristic (ROC) curve, *Radiology* **143**, 29–36.

Heye, C.: 1993, Labor market tightness and business confidence: An international comparison, *Politics and Society* **21**, 169–193.

Jorgenson, D. W.: 1963, Capital theory an investment behavior, *American Economic Review Papers and Proceedings* **59**, 247–259.

Kauppi, H. and Saikkonen, P.: 2008, Predicting US recessions with dynamic binary response models, *Review of Economics and Statistics* **90**, 777–791.

Keynes, J. M.: 1936, *The General Theory of Employment, Interest, and Money*, Palgrave McMillan.

Lahiri, K., Monokroussos, G. and Zhao, Y.: 2016, Forecasting consumption: The role of consumer confidence in real time with many predictors, *Journal of Applied Econometrics* **31**, 1254–1275.

Leeper, E.: 1992, Consumer attitudes: King for a day, *Federal Reserve Bank of Atlanta Economic Review* pp. 1–15.

Liu, W. and Moench, E.: 2016, What predicts US recessions?, *International Journal of Forecasting* **32**, 1138–1150.

Ludvigson, S. C.: 2004, Consumer confidence and consumer spending, *Journal of Economic Perspectives* **18**, 29–50.

Matsusaka, J. G. and Sbordone, A. M.: 1995, Consumer confidence and economic fluctuations, *Economic Inquiry* **32**, 296–318.

Nyberg, H.: 2010, Dynamic probit models and financial variables in recession forecasting, *Journal of Forecasting* **29**, 215–230.

Nyberg, H.: 2011, Forecasting the direction of the US stock market with dynamic binary probit models, *International Journal of Forecasting* **27**, 561–578.

Pesaran, M. H. and Timmermann, A.: 2009, Testing dependence among serially correlated multicategory variables, *Journal of the American Statistical Association* **485**, 325–337.

Pönkä, H.: 2017a, Predicting the direction of US stock markets using industry returns, *Empirical Economics* **52**, 1451–1480.

Ponka, H.: 2017b, The role of credit in predicting US recessions, *Journal of Forecasting* **36**, 469–482.

Rapach, D. E. and Wohar, M. E.: 2007, Forecasting the recent behavior of US business fixed investment spending: An analysis of competing models, *Journal of Forecasting* **26**, 33–51.

Rossi, B.: 2013, Advances in forecasting under model instability, *Handbook of Economic Forecasting* **2**, 1203–1324.

Taylor, K. and McNabb, R.: 2007, Business cycles and the role of confidence: Evidence for Europe, *Oxford Bulletin of Economics and Statistics* **69**, 185–208.

8 Appendix

8.1 Data construction and source

Business confidence index: We obtain the business confidence index from the OECD's leading indicator database. The OECD collects business confidence data, based on business tendency survey of manufacturing activity, from the Institute for Supply Management (ISM).[21] The business confidence series refers to PMI (previously, PMI referred to the Purchasing Managers' Index), which is based on Manufacturing ROB. The PMI is an equally weighted (20% each) composite index of five seasonally adjusted diffusion indices, namely, new orders, production, employment, supplier deliveries and inventories. An index value of over 50 represents growth or expansion within the manufacturing sector of the economy compared with the prior month and a value of under 50 indicates contraction. The OECD converts the PMI diffusion index into a net balance (in %) for cross-country consistency.

Real business investment and its components: The real business investment corresponds to the private non-residential fixed investment and its components are non-residential structure, equipment and intellectual property products. We obtain the data from NIPA Table 1.1.3 of BEA.

Real gross domestic product: We obtain the data for the real gross domestic product from NIPA Table 1.1.3 of BEA.

Price index of gross domestic product: We obtain the data for the price index of real gross domestic product from NIPA Table 1.1.4 of BEA

Price index of business investment: We obtain the data for the price index of real business investment from NIPA Table 1.1.4 of BEA

Real lending rate: It is the prime business rate of commercial bank. We obtain the data from Economic Research Division, Federal Reserve Bank of St. Louis. Source: Board of Governors of the Federal Reserve System.

We calculate the real lending rate as an ex post measure as follows:

$$R_t = (i/100) - \log(\text{Price index of}\, GDP_{t+1}/\text{Price index of}\, GDP_t) \tag{17}$$

, where, R is the real lending rate.

[21] http://www.ism.ws/ISMReport/MfgROB.cfm?navItemNumber=12942

User cost of capital: We measure the user cost of capital following Chirinko and Schaller (2001) and Ang (2010), which is similar to the Hall and Jorgenson (1969). The user cost of capital is as follows:

$$CC_t = (R_t + DEP_t)(\text{Price index of}\, TBI_t/\text{Price index of}\, GDP_t) \tag{18}$$

where, DEP is the depreciation. We fix the DEP as 5%.

Real cash flow: It is the net cash flow with Inventory Valuation Adjustment (IVA) divided by the price index of gross domestic product. We obtain from Economic Research Division, Federal Reserve Bank of St. Louis. Source: BEA.

Stock market price: It is the monthly S&P 500 index divided by the price index of gross domestic product. We collect from Yahoo!Finance.[22]

Term spread: It is the monthly rate of 10-year government bond minus the monthly rate of 3-month treasury bill. We obtain from Economic Research Division, Federal Reserve Bank of St. Louis. Source: Board of Governors of the Federal Reserve System.

Credit spread: It is the Moody's Baa corporate bond yield minus the Moody's Aaa corporate bond yield. We obtain from Economic Research Division, Federal Reserve Bank of St. Louis. Source: Board of Governors of the Federal Reserve System.

8.2 SR calculation

The calculation of SR is as:

$$SR = \frac{\hat{g}^{uu} + \hat{g}^{dd}}{\hat{g}^{uu} + \hat{g}^{du} + \hat{g}^{ud} + \hat{g}^{dd}}, \tag{19}$$

where, $\hat{g}_t$, u and d are the forecast of g_t, upward signal and downward signal, respectively.

$$\hat{g}^{uu} = \sum_{t=1}^{T} \mathbf{1}[\hat{g}_t = 1, g_t = 1],$$

$$\hat{g}^{ud} = \sum_{t=1}^{T} \mathbf{1}[\hat{g}_t = 1, g_t = 0],$$

$$\hat{g}^{du} = \sum_{t=1}^{T} \mathbf{1}[\hat{g}_t = 0, g_t = 1],$$

[22] https://finance.yahoo.com/q/hp?s=%5EGSPC+Historical+Prices

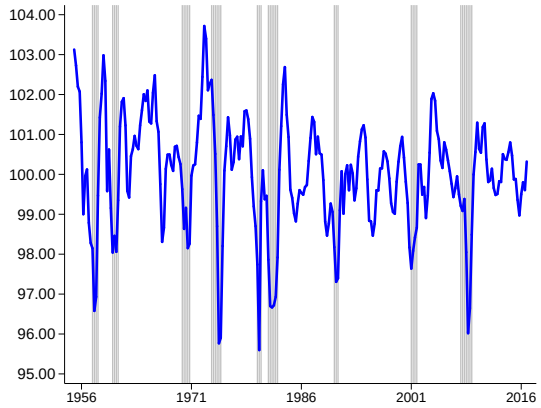
$$\hat{g}^{dd} = \sum_{t=1}^{T} \mathbf{1}[\hat{g}_t = 0, g_t = 0]$$

8.3 Additional models for downturns and direction of investment

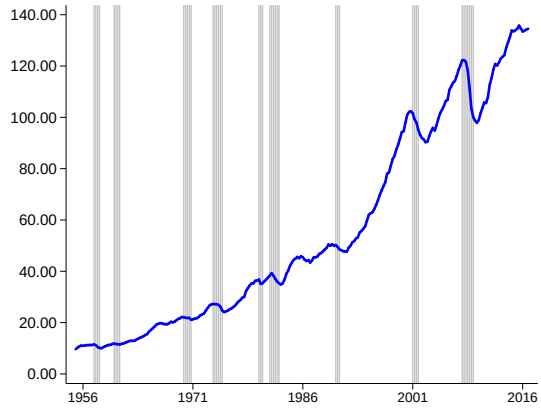
Table 13 contains the results to assess the robustness whether BCI has independent forecasting power for business investment downturns, after controlling for other relevant predictors. Panel (a) shows that BCI-nested model performs better than BCI non-nested model for 1–4 quarter horizons. The result suggests that BCI has additional information to forecast investment downturns, after controlling for conventional predictors, TS and ΔSP of recessions. Panel (b) shows that BCI-nested model is superior than BCI non-nested model for all forecast horizons, where we control for CS and ΔSP. We next consider CS, ΔSP and ΔGDP as control variables and show the results in panel (c). This result is also consistent with previous result and implies that BCI has independent information to forecast the investment downturns for 1–4 quarter horizons.

Finally, we use different control variables to evaluate whether BCI forecast for direction of investment growth independently. Table 14 shows the results. Panel (a) shows that BCI-nested model is better than BCI non-nested model for 1and 3 quarter forecast horizons, suggesting that BCI has independent information to explain the direction of investment, controlling for conventional predictors, TS and ΔSP. We then control for CS and ΔSP and show the results in panel (b). The results show that BCI-nested model has better performance than BCI non-nested model for 1 and 4 quarter horizons. Panel (c) also shows the results after controlling for three predictors, CS, ΔSP and ΔGDP and suggests that BCI has additional information to explain the direction of investment for 2 quarter horizons.

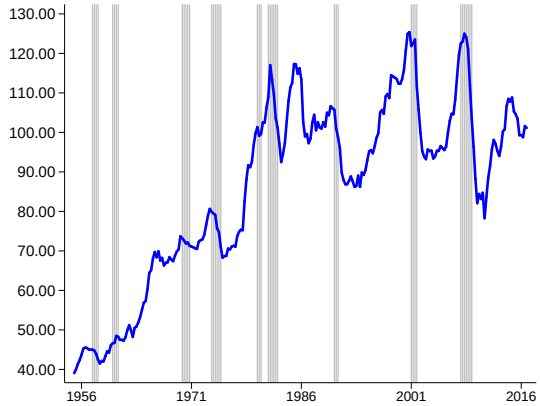
Figure 1: Main data used in the analysis



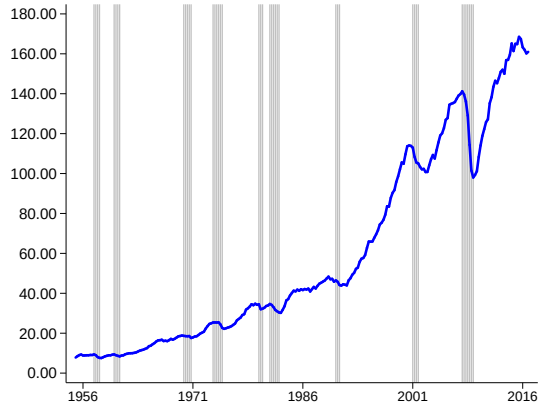
(a) Business Confidence Index



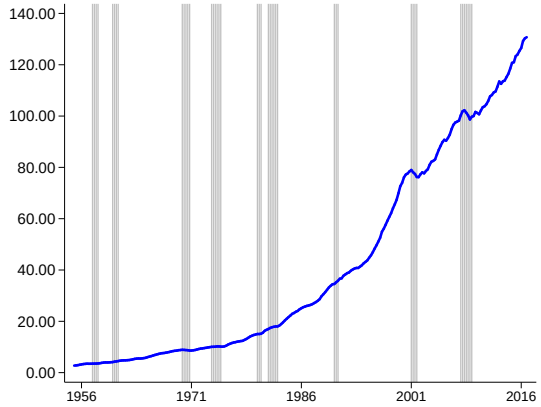
(b) Total Business Investment



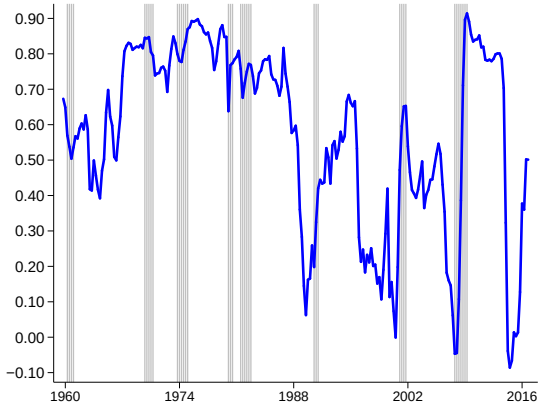
(c) Structures Investment



(d) Equipment Investment



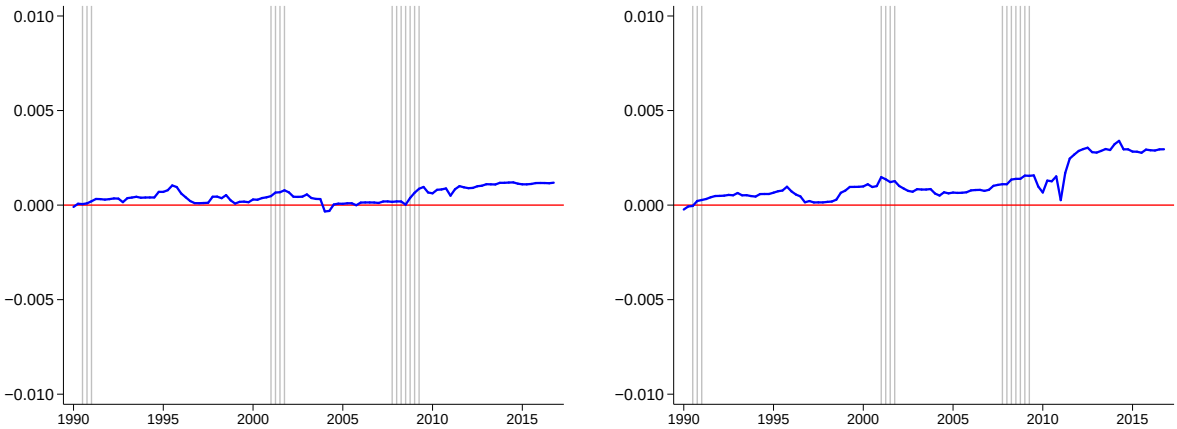
(e) Intellectual Property Products Investment



(f) Rolling-window correlations BCI and ΔTBI

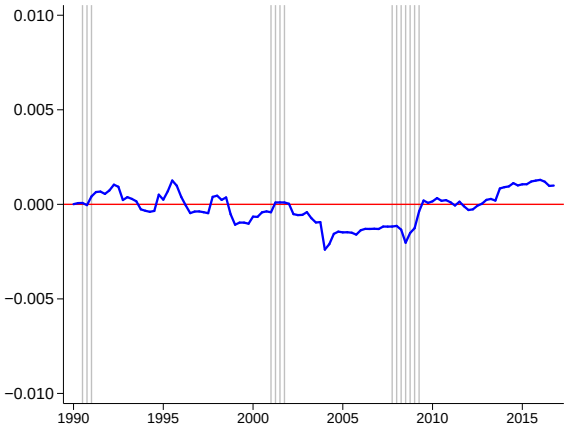
Note: The NBER recession dates are in grey shading. Panels (a–e) show the main data used in analysis and the data series are in levels. Panel (f) shows the 20–quarters rolling window correlations of BCI and ΔTBI.

Figure 2: CDSFE: OOS predictive ability of BCI for investment growth

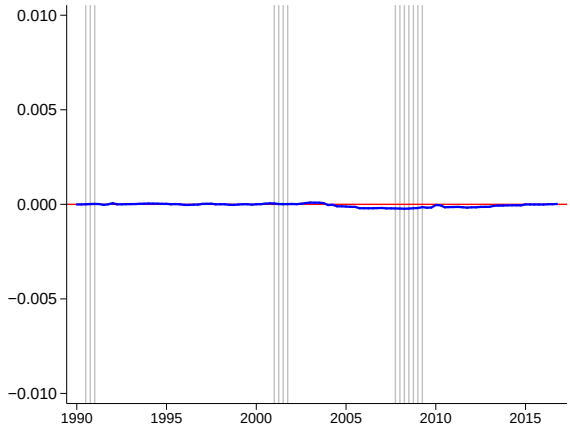


(a) ΔTBI

(b) ΔSI



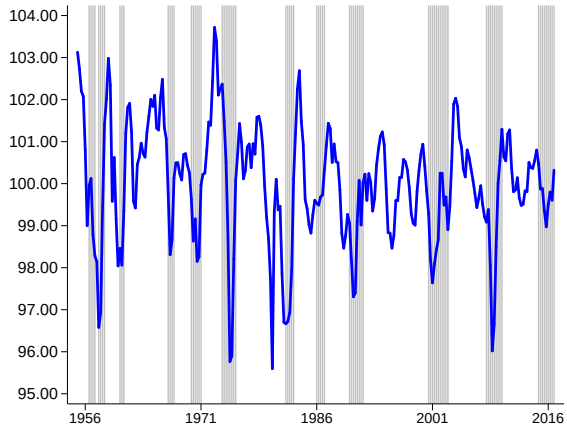
(c) ΔEI



(d) ΔIPI

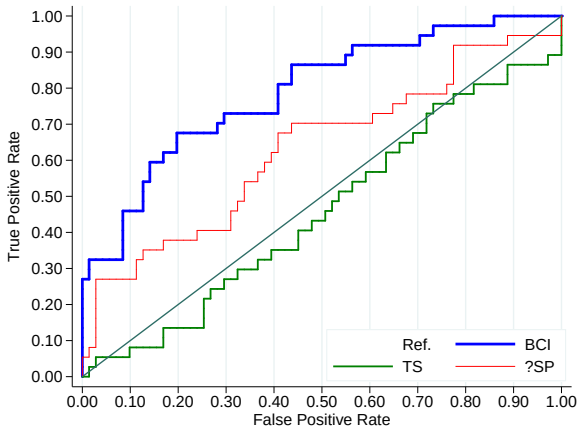
Note: The OOS period is 1990Q1–2016Q4. We show CDSFE, which is cumulative squared forecast errors from baseline model minus cumulative squared forecast errors from BCI-nested model. A positive value of CDSFE shows that the BCI-nested model outperform the baseline model. The NBER recession dates are in grey shading

Figure 3: BCI and investment downturns

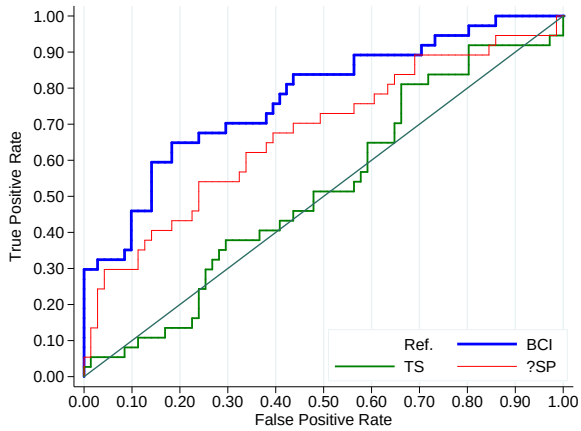


Note: The defined investment downturns are in grey shading. We define investment downturns as the total business investment growth is below the sample average for more than two consecutive quarters (see Taylor and McNabb (2007) The sample average investment growth rate is 1.07 percent for the period 1955Q1–2016Q4.

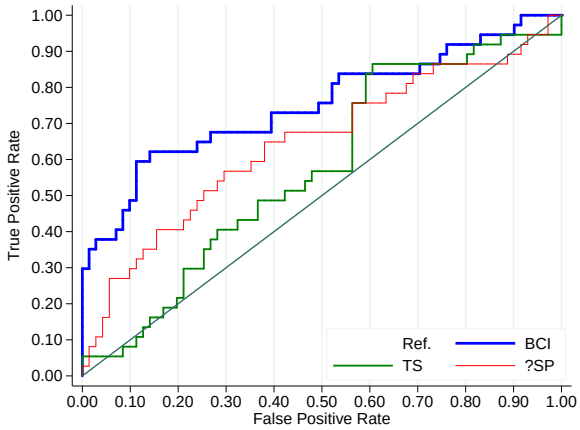
Figure 4: OOS ROC curves



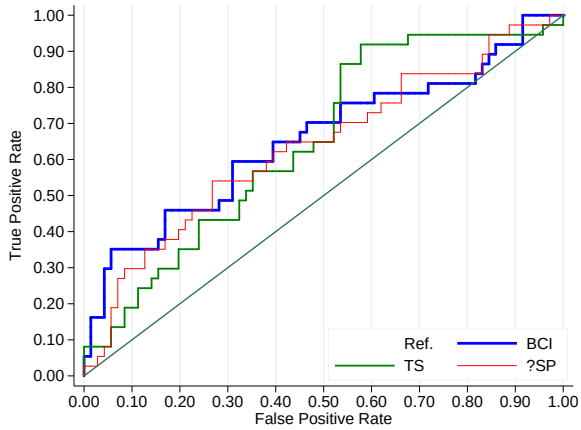
(a) 1–quarter forecast horizon



(b) 2–quarter forecast horizon



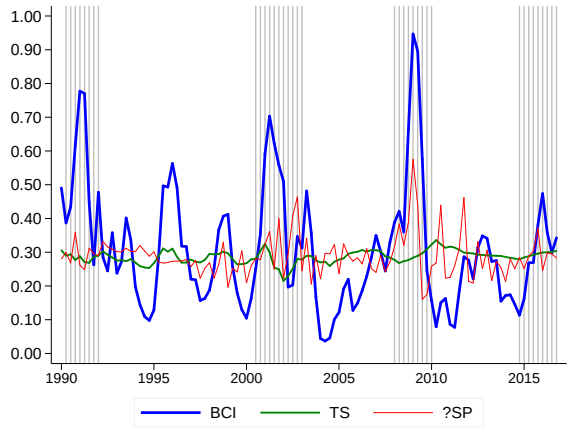
(c) 3–quarter forecast horizon



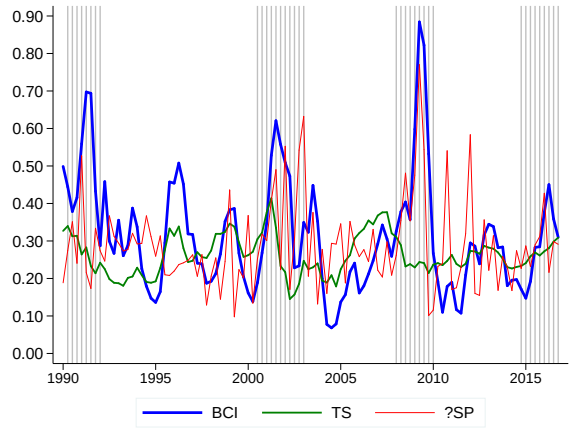
(d) 4–quarter forecast horizon

Note: The OOS period is 1990Q1–2016Q4. We plot the ROC curves for BCI, TS and ΔSP for 1–4 quarter forecast horizons. The 45° line represents a coin-toss classifier. The ROC curve plots all possible combinations of true positive rates and false positive rates using various possible threshold values from 0 to 1.

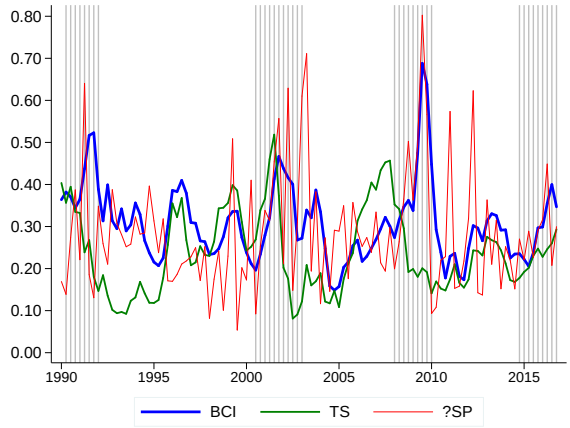
Figure 5: OOS predicted investment downturns probabilities



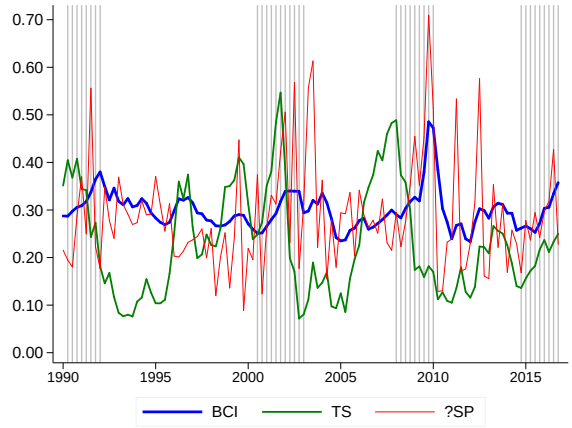
(a) 1–quarter forecast horizon



(b) 2–quarter forecast horizon



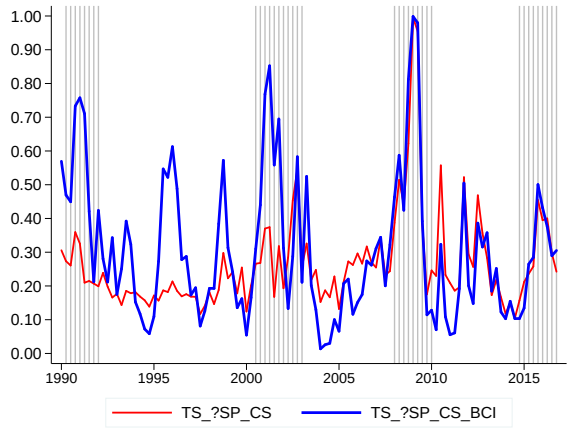
(c) 3–quarter forecast horizon



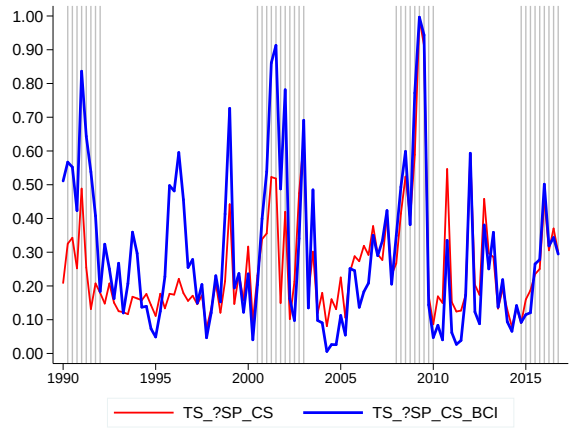
(d) 4–quarter forecast horizon

Note: The OOS period is 1990Q1–2016Q4. We plot OOS predicted investment downturns probabilities for BCI, TS and ΔSP for 1–4 quarter forecast horizons. The defined downturn dates are in grey shading.

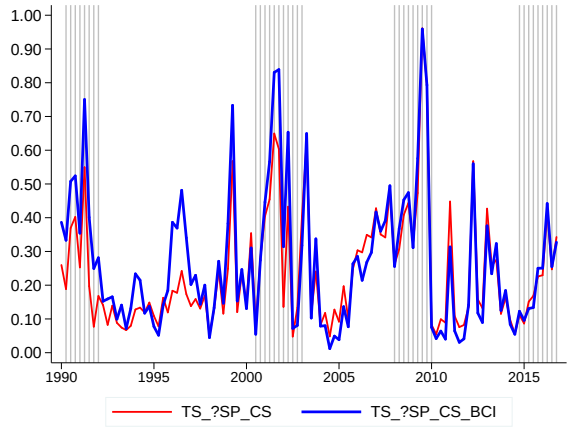
Figure 6: OOS predicted investment downturns probabilities



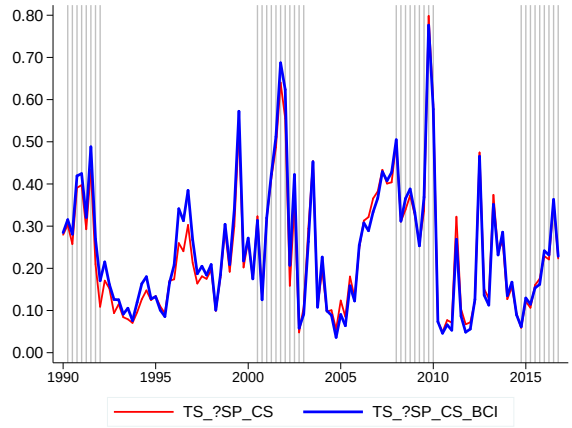
(a) 1–quarter forecast horizon



(b) 2–quarter forecast horizon



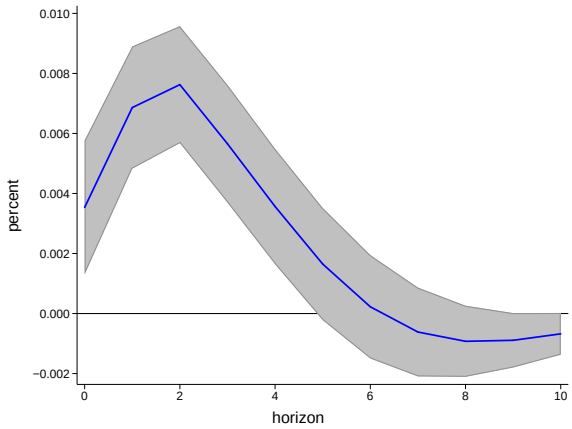
(c) 3–quarter forecast horizon



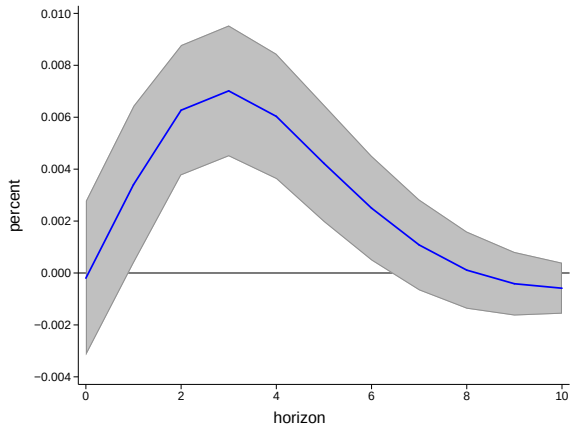
(d) 4–quarter forecast horizon

Note: The OOS period is 1990Q1–2016Q4. We plot the predicted investment downturns probabilities for BCI non-nested model and BCI-nested model for 1–4 quarter horizons. The defined downturn dates are in grey shading.

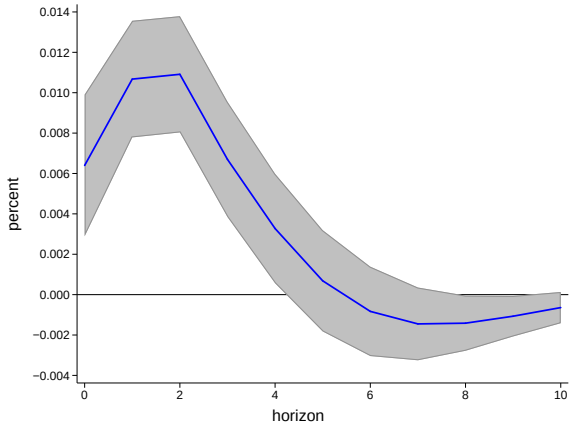
Figure 7: Impulse responses of investment growth and its components to BCI (ordered first) shock



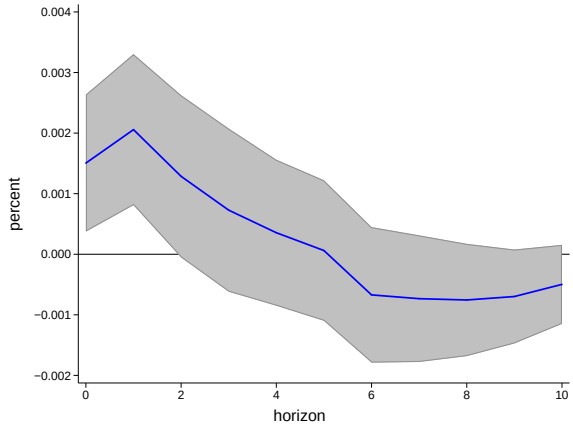
(a) ΔTBI to BCI



(b) ΔSI to BCI



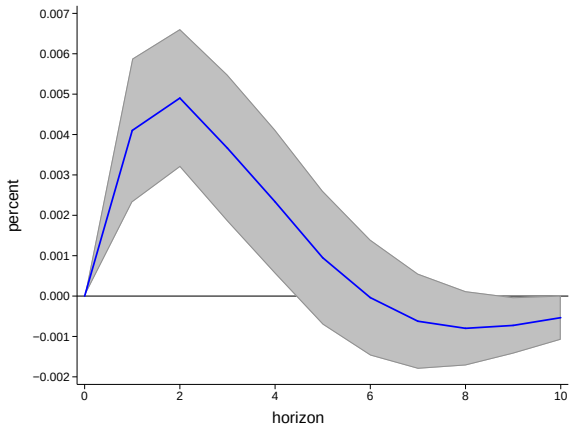
(c) ΔEI to BCI



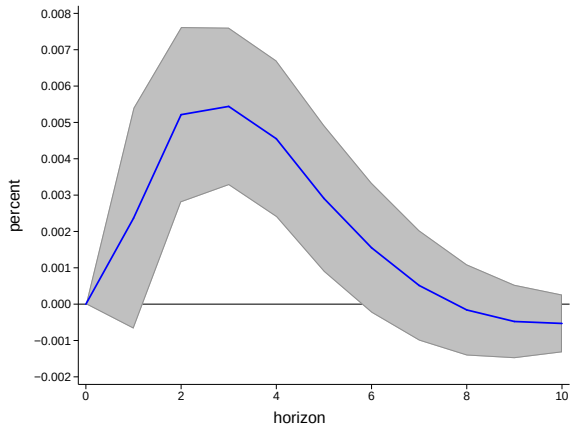
(d) ΔIPI to BCI

Note: These are impulse responses of investment growth and its components to one standard deviation positive innovation in VAR. We order BCI at first in VAR system. The grey shading areas indicate bootstrap confidence bands at 95% level.

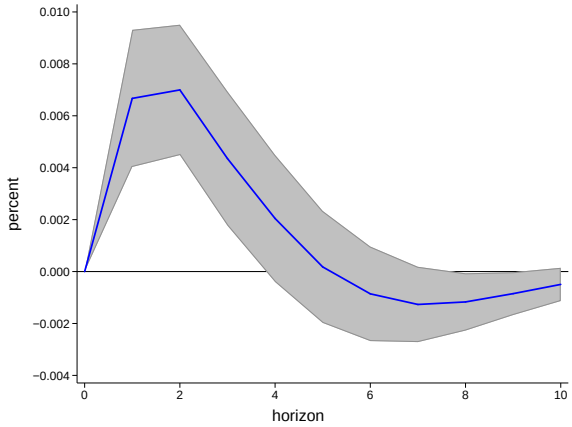
Figure 8: Impulse responses of investment growth and its components to BCI (ordered last) shock



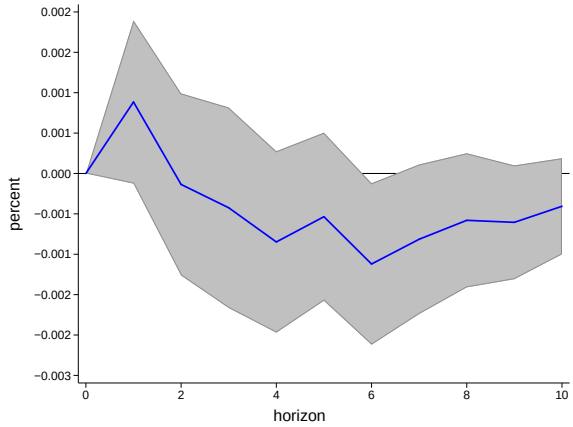
(a) ΔTBI to BCI



(b) ΔSI to BCI



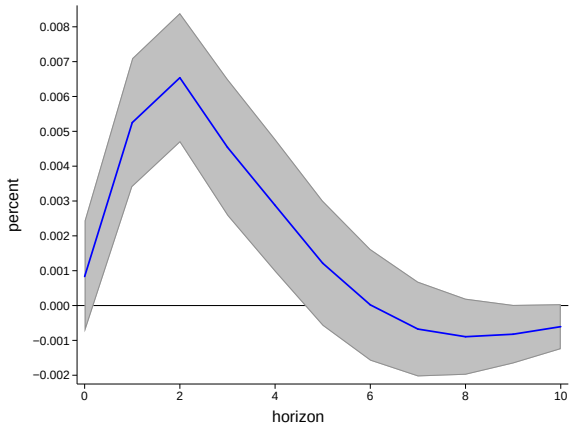
(c) ΔEI to BCI



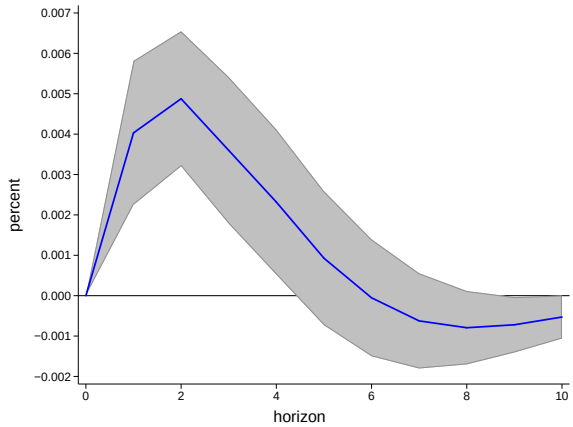
(d) ΔIPI to BCI

Note: These are impulse responses of investment growth and its components to one standard deviation positive innovation in VAR. We order BCI at last in VAR system. The grey shading areas indicate bootstrap confidence bands at 95% level.

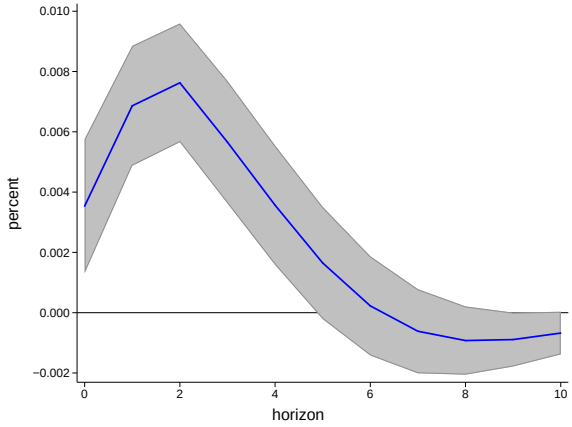
Figure 9: Ordering free VAR: Impulse responses of ΔTBI to a BCI shock



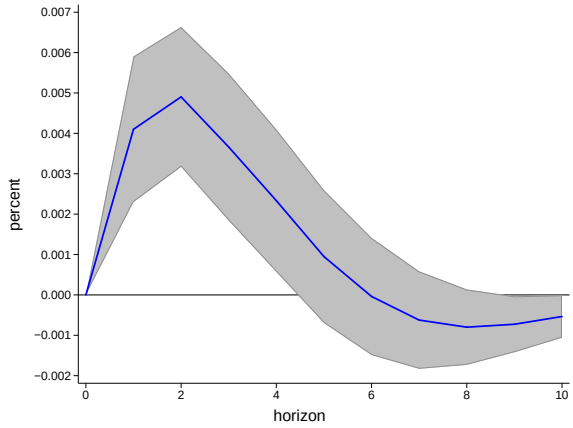
(a) ΔTBI to BCI



(b) ΔTBI to BCI



(c) ΔTBI to BCI



(d) ΔTBI to BCI

Note: These are impulse responses of ΔTBI to one standard deviation positive innovation of BCI. We use six variables in VAR structure and order the variables randomly. In Panel (a), we order ΔGDP, BCI, ΔCF, ΔSP, ΔTBI and ΔCC; in Panel (b) ΔTBI, ΔGDP, ΔCF, ΔSP, BCI and ΔCC; in Panel (c) BCI, ΔSP, ΔTBI, ΔGDP, ΔCF and ΔCC; and in Panel (d) ΔSP, ΔGDP, ΔTBI, ΔCF, ΔCC and BCI. The grey shading areas indicate bootstrap confidence bands at 95% level.

Table 2: In-sample results: Predictive ability of BCI for investment growth

	(a) Baseline		(b) BCI-nested	
Category of investment	$\bar{R}^2$	p-value	Incremental $\bar{R}^2$	p-value
ΔTBI	.459	.000	.067	.000
ΔSI	.287	.000	.020	.050
ΔEI	.383	.000	.075	.000
ΔIPI	.460	.000	.006	.121

Note: We report $\bar{R}^2$ for baseline model without BCI and p-values of the joint significance of all explanatory variables excluding intercept in panel (a). We report increment of $\bar{R}^2$ ($\bar{R}^2$ from BCI-nested model minus $\bar{R}^2$ from baseline model) and p-values of the joint significance of the lags of BCI for BCI–nested model in panel (b). We determine the number of lags for each regression using AIC and set four as maximum lags. To estimate ΔTBI and ΔEI, we use 2 lags. We use 3 lags and 4 lags to estimate ΔSI and ΔIPI, respectively. We use Newey-West estimator with four lags.

Table 3: OOS results: Predictive ability of BCI for investment growth

Category of investment	R^2_{OS}	p-value
ΔTBI	.052***	.006
ΔSI	.033**	.044
ΔEI	.016**	.012
ΔIPI	.002	.227

Note: The OOS results are based on one-step-ahead forecasts for 1990Q–2016Q4. A positive R^2_{OS} indicates that the addition of BCI in prediction equation helps forecast the future investment growth. We report the p-value of the Clark and West (2007) statistics corresponding to a test that the null hypothesis of $R^2_{OS} \leq 0$ against $R^2_{OS} > 0$. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 4: OOS results: Predictive ability of predictors for investment downturns

$\pi_t = \omega + \psi X_{t-k}$					
Predictors	Forecasting Measures	$k = 1$	$k = 2$	$k = 3$	$k = 4$
BCI	ps.R^2	**.277**	**.252**	**.220**	**.099**
	QPS	**.343**	**.358**	**.390**	.434
	AUC	**.790*** **	**.774*** **	**.751*** **	**.655*** **
TS	ps.R^2	.014	.000	012	.055
	QPS	.462	.467	.470	.450
	AUC	.456	.519	.574	.649***
ΔSP	ps.R^2	.065	.109	.070	.054
	QPS	.433	.410	.425	.432
	AUC	.631**	.674***	.645**	.636**
CS	ps.R^2	.214	.118	.035	.029
	QPS	.393	.419	.443	.462
	AUC	.766***	.683***	.551	.359**
ΔGDP	ps.R^2	.182	.179	.142	.085
	QPS	.372	.378	.399	**.424**
	AUC	.745***	.747***	.710***	.654***
ΔCC	ps.R^2	.127	.063	.017	.028
	QPS	.418	.439	.461	.461
	AUC	.676***	.620**	.434	.404
ΔCF	ps.R^2	.024	.005	.008	.001
	QPS	.516	.508	.486	.485
	AUC	.410	.475	.458	.501

Note: The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. The best forecast for each horizon is in bold. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 5: OOS results: Predictive ability of BCI for investment downturns, using control variables

	Without BCI				With BCI			
	$k=1$	$k=2$	$k=3$	$k=4$	$k=1$	$k=2$	$k=3$	$k=4$
$\pi_t = \omega + \delta_1 TS_{t-k} + \delta_2 \Delta SP_{t-k} + \delta_3 CS_{t-k} + \phi BCI_{t-k}$								
ps.R^2	.209	.188	.123	.138	**.263**	**.238**	**.166**	**.154**
QPS	.387	.388	.417	.414	**.340**	**.349**	**.387**	**.404**
AUC	.780***	.748***	.700***	.712***	**.785*** **	**.768*** **	**.727*** **	**.722*** **

Note: The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. The results are in bold if the forecast result is better from BCI nested model than non-nested model for each forecast horizon. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 6: OOS results: Predictive ability of predictors for direction of investment growth

$\Pi_t = \varphi + \kappa V_{t-k}$					
Predictors	Forecasting Measures	$k = 1$	$k = 2$	$k = 3$	$k = 4$
BCI	ps.R^2	.231	**.247**	**.229**	.057
	QPS	**.299**	**.312**	**.339**	.372
	AUC	.768***	**.775*** **	**.776*** **	**.670*** **
	SR	**.833*** **	**.796* **	**.759* **	**.741**
TS	ps.R^2	.063	.012	.001	.032
	QPS	.394	.397	.391	.372
	AUC	.367**	.414	.530	.616*
	SR	.741	.741	.741	.741
ΔSP	ps.R^2	.044	.074	.081	**.071**
	QPS	.371	.354	.352	**.357**
	AUC	. 637*	.641**	.666**	.639**
	SR	.741	.769	.741	.759*
CS	ps.R^2	**.265**	.139	.036	.000
	QPS	.319	.348	.374	.388
	AUC	**.800*** **	.722***	.570	.479
	SR	.767	.759	**.759* **	.741
ΔGDP	ps.R^2	.177	.176	.116	.026
	QPS	.321	.331	.351	.379
	AUC	.736***	.741***	.669***	.608*
	SR	.806**	.787	**.759* **	.741
ΔCC	ps.R^2	.097	.063	.031	.057
	QPS	.360	.377	.390	.393
	AUC	.671***	.644**	.409	.342**
	SR	.75**	.741	.741	.741
ΔCF	ps.R^2	.006	.013	.031	.006
	QPS	.460	.431	.409	.392
	AUC	.456	.420	.373*	.447
	SR	.676	.713	.731	.741

Note: The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. SR is the percentage of correct forecast. We perform PT test that the null hypothesis is that the value of SR does not differ from the ratio that would be obtained in the case of no predictability, when realized value (g_t) and sign forecasts ($\hat{g}_t$) are independent. The best forecast for each horizon is in bold. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 7: OOS results: Predictive ability of BCI for direction of investment growth, using control variables

	Without BCI				With BCI			
	$k=1$	$k=2$	$k=3$	$k=4$	$k=1$	$k=2$	$k=3$	$k=4$
$\Pi_t = \varphi + \theta_1 TS_{t-k} + \theta_2 \Delta SP_{t-k} + \theta_3 CS_{t-k} + \vartheta BCI_{t-k}$								
ps.R^2	.185	.128	.118	.118	**.215**	**.188**	**.167**	**.132**
QPS	.321	.330	.337	.339	**.301**	**.309**	**.319**	**.334**
AUC	.727***	.684***	.699***	.720***	**.759*** **	**.738*** **	**.734*** **	**.733*** **
SR	.768	.787	.759	.75	**.805*** **	**.796* **	**.778* **	**.759**

Note: The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and we consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. SR is the percentage of correct forecast. We perform PT test that the null hypothesis is that the value of SR does not differ from the ratio that would be obtained in the case of no predictability, when realized value (g_t) and sign forecasts ($\hat{g}_t$) are independent. The results are in bold if the forecast result is better from BCI nested model than non-nested model for each forecast horizon. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 8: In-sample results: Predictive ability of BCI for investment growth

	(a) Baseline		(b) BCI-nested	
Category of investment	$\bar{R}^2$	p-value	Incremental $\bar{R}^2$	p-value
ΔTBI	.474	.000	.066	.000
ΔSI	.285	.000	.010	.127
ΔEI	.402	.000	.081	.000
ΔIPI	.437	.000	.027	.022

Note: We report $\bar{R}^2$ for baseline model without BCI and p-values of the joint significance of all explanatory variables excluding intercept in panel (a). We report increment of $\bar{R}^2$ ($\bar{R}^2$ from BCI-nested model minus $\bar{R}^2$ from baseline model) and p-values of the joint significance of the lags of BCI for BCI–nested model in panel (b). We determine the number of lags for each regression using AIC and set four as maximum lags. To estimate ΔTBI and ΔEI, we use 2 lags. We use 3 lags and 4 lags to estimate ΔSI and ΔIPI, respectively. We use Newey-West estimator with four lag window.

Table 9: OOS results: Predictive ability of BCI for investment growth

Category of investment	R^2_{OS}	p-value
ΔTBI	.055**	.012
ΔSI	.021*	.064
ΔEI	.009**	.027
ΔIPI	-.019	.224

Note: The OOS results are based on one-step-ahead forecasts for 1990Q–2016Q4. A positive R^2_{OS} indicates that the addition of BCI in prediction equation helps forecast the future investment growth. We report the p-value of the Clark and West (2007) statistics corresponding to a test that the null hypothesis of $R^2_{OS} \leq 0$ against $R^2_{OS} > 0$. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 10: OOS results: Predictive ability of BCI for investment downturns†

$\pi_t = \omega + \psi X_{t-k}$					
Predictor	Forecasting Measures	$k = 1$	$k = 2$	$k = 3$	$k = 4$
BCI	ps.R^2	.417	.459	.312	.082
	QPS	.222	.235	.265	.308
	AUC	.890***	.909***	.899***	.796***

Note: † indicates the alternative downturns which is one if the total investment growth is negative for more than two consecutive quarter and otherwise zero. The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The overall set up of the estimation is similar to the subsection 4.1. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 11: In-sample results, using different converting approach of monthly to quarterly BCI data: Predictive ability of BCI for investment growth

	(a) Baseline	(b) BCI-nested		(c) BCI-nested		(d) BCI-nested	
Category		Incremental		Incremental		Incremental	
of investment	$\bar{R}^2$	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value
ΔTBI	.459	.051	.000	032	.000	.059	.000
ΔSI	.287	.017	.069	.014	.089	.019	.055
ΔEI	.383	.055	.000	.031	.002	.065	.000
ΔIPI	.460	-.003	.610	.004	.298	-.001	.339

Note: We report $\bar{R}^2$ for baseline model without BCI in Panel (a). We report increment of $\bar{R}^2$ ($\bar{R}^2$ from BCI-nested model minus $\bar{R}^2$ from baseline model) and p-values of the joint significance of the lags of BCI for BCI–nested model in panel (b–d). We use BCI quarterly data by taking average of three months in Panel (b). We use each first month of the quarter to convert quarterly data in Panel (c) and use weighted average of 0.1, 0.3 and 0.6 of first, second and third month, respectively, in Panel (d). We determine the number of lags for each regression using AIC and set four as maximum lags. To estimate ΔTBI and ΔEI, we use 2 lags. We use 3 lags and 4 lags to estimate ΔSI and ΔIPI, respectively. We use Newey-West estimator with four lag window.

Table 12: OOS results from dynamic probit: Predictive ability of BCI for investment downturns, using control variables

	Without BCI				With BCI			
	$k=1$	$k=2$	$k=3$	$k=4$	$k=1$	$k=2$	$k=3$	$k=4$
$\pi_t = \omega + \zeta d_{t-k-3} + \delta_1 TS_{t-k} + \delta_2 \Delta SP_{t-k} + \delta_3 CS_{t-k} + \phi BCI_{t-k}$								
ps.R^2	.264	.185	.101	.116	**.328**	**.228**	**.128**	**.125**
QPS	.371	.388	.423	.416	**.315**	**.352**	**.404**	**.409**
AUC	.812***	.724***	.672***	.687***	**.824*** **	**.764*** **	**.690*** **	**.696*** **

Note: The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. The results are in bold if the forecast result is better from BCI nested model than non-nested model for each forecast horizon. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 13: OOS results: Predictive ability of BCI for investment downturns, using control variables

	Without BCI				With BCI			
	$k=1$	$k=2$	$k=3$	$k=4$	$k=1$	$k=2$	$k=3$	$k=4$
A: $\pi_t = \omega + \delta_1 TS_{t-k} + \delta_2 \Delta SP_{t-k} + \phi BCI_{t-k}$								
ps.R^2	.052	.106	.086	.119	**.275**	**.266**	**.174**	**.156**
QPS	.436	.416	.431	.402	**.338**	**.341**	**.385**	.403
AUC	.641**	.688***	.681***	.704***	**.790*** **	**.784*** **	**.736*** **	**.729*** **
B: $\pi_t = \omega + \delta_1 CS_{t-k} + \delta_2 \Delta SP_{t-k} + \phi BCI_{t-k}$								
ps.R^2	.236	.177	.090	.048	**.282**	**.247**	**.160**	**.084**
QPS	.376	.383	.415	.434	**.332**	**.343**	**.380**	**.416**
AUC	.807***	.734***	.660***	.616**	.790***	**.776*** **	**.724*** **	**.657*** **
C: $\pi_t = \omega + \delta_1 CS_{t-k} + \delta_2 \Delta SP_{t-k} + \delta_3 \Delta GDP_{t-k} + \phi BCI_{t-k}$								
ps.R^2	.254	.230	.140	.083	**.301**	**.273**	**.171**	**.085**
QPS	.344	.352	.389	.414	**.323**	**.332**	**.375**	.414
AUC	.786***	.768***	.708***	.648***	**.795*** **	**.784*** **	**.729*** **	**.652*** **
D: $\pi_t = \omega + \delta V_{t-k} + \phi BCI_{t-k}$								
ps.R^2	.253	**.231**	**.201**	**.145**	**.283**	.228	.197	.137
QPS	.347	.727	.628	**.405**	**.330**	**.523**	**.518**	.410
AUC	.784***	**.785*** **	**.752*** **	**.703*** **	**.788*** **	.761***	.747***	.693***

Note: The OOS period is 1990Q1–2016Q4. We use k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. The results are in bold if the forecast result is better from BCI nested model than non-nested model for each forecast horizon. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 14: OOS results: Predictive ability of BCI for direction of investment growth, using control variables

	Without BCI				With BCI			
	$k=1$	$k=2$	$k=3$	$k=4$	$k=1$	$k=2$	$k=3$	$k=4$
A: $\Pi_t = \varphi + \theta_1 TS_{t-k} + \theta_2 \Delta SP_{t-k} + \vartheta BCI_{t-k}$								
ps.R^2	.016	.062	.072	.110	**.215**	**.192**	**.168**	**.141**
QPS	.378	.358	.355	.344	**.300**	**.306**	**.319**	**.332**
AUC	.568	.613	.662**	.705***	**.756*** **	**.738*** **	**.739*** **	**.734*** **
SR	.741	.759	.759	.750	**.796** **	**.778**	**.778* **	**.759**
B: $\Pi_t = \varphi + \theta_1 CS_{t-k} + \theta_2 \Delta SP_{t-k} + \vartheta BCI_{t-k}$								
ps.R^2	.272	.139	.105	.065	.250	**.208**	**.189**	**.098**
QPS	.306	.327	.342	.359	**.291**	**.305**	**.319**	**.347**
AUC	.810***	.698***	.668**	.634**	.777***	**.776*** **	**.762*** **	**.683*** **
SR	.768	.787	.768	.741	**.787*** **	.787	**.778**	**.778* **
C: $\Pi_t = \varphi + \theta_1 CS_{t-k} + \theta_2 \Delta SP_{t-k} + \theta_3 \Delta GDP_{t-k} + \vartheta BCI_{t-k}$								
ps.R^2	.261	.188	.140	.072	**.273**	**.222**	**.173**	**.094**
QPS	.291	.311	.332	.356	**.284**	**.300**	**.322**	**.349**
AUC	.789***	.737***	.706***	.639**	.786***	**.758*** **	**.742*** **	**.677*** **
SR	.824***	.787	.778	.741	**.833*** **	**.806** **	.778	**.768**

Note: The OOS period is 1990Q1–2016Q4. We denote k to denote the forecast horizon and consider 1–4 quarter forecast horizons. The value of ps.R^2 is between 0 and 1 that corresponds to "no fit" and "perfect fit", respectively. The QPS ranges from 0 to 2. The QPS is 0 that corresponds to perfect accuracy. The value of AUC is one indicates that there is perfect downturns classifier. SR is the percentage of correct forecast. We perform PT test that the null hypothesis is that the value of SR does not differ from the ratio that would be obtained in the case of no predictability, when realized value (g_t) and sign forecasts ($\hat{g}_t$) are independent. The results are in bold if the forecast result is better from BCI nested model than non-nested model for each forecast horizon. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 15: Baseline forecast of business investment growth

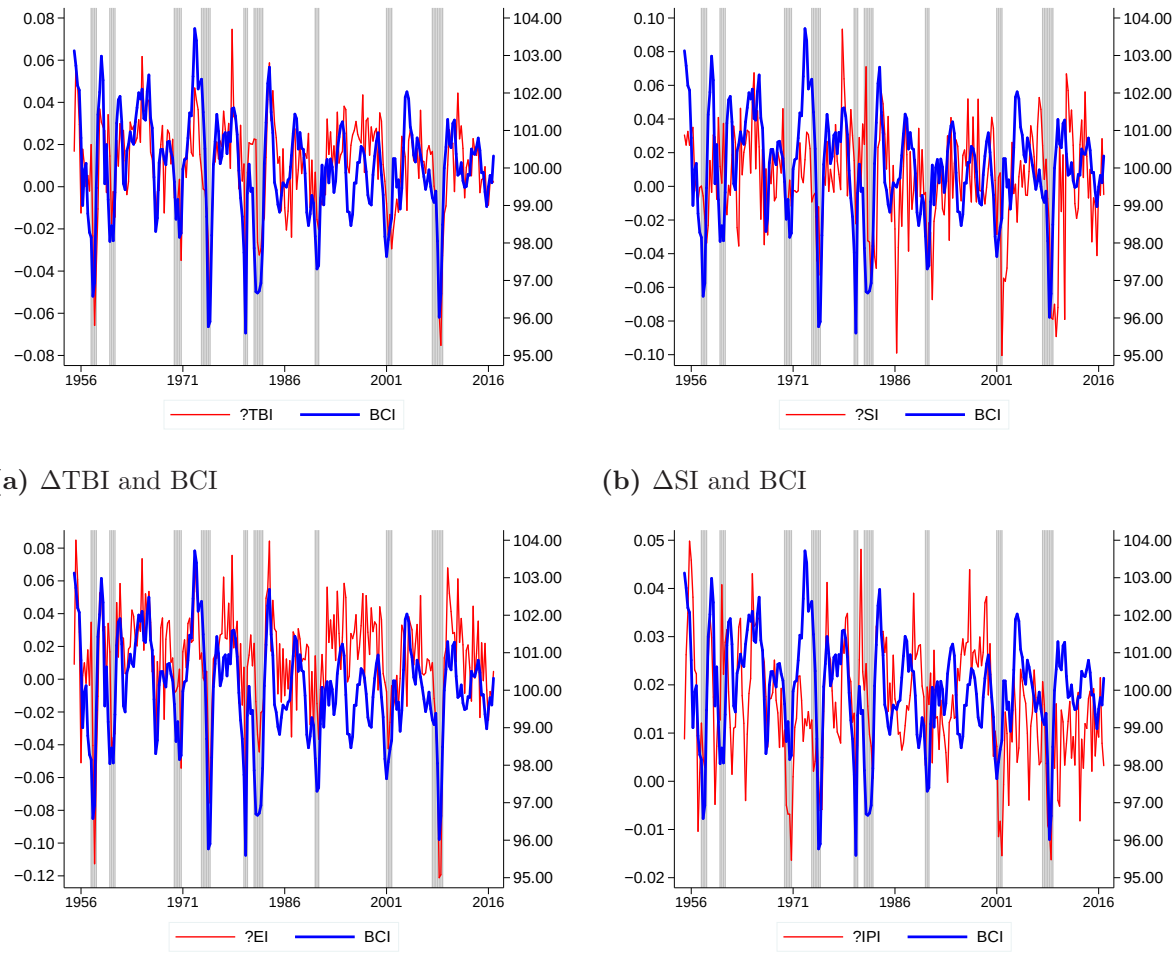
Variables	lags of dependent variable	lags of ΔGDP	lags of ΔCC	lags of ΔCF	lags of ΔSP	$\bar{R}^2$
ΔTBI	.468	.508	.007	.088	.099	0.459
	(.000)	(.030)	(.513)	(.061)	(.000)	
ΔSI	.261	.057	.103	-.099	.115	0.287
	(.001)	(.005)	(.040)	(.119)	(.020)	
ΔEI	.352	.672	.011	.181	.161	0.383
	(.007)	(.055)	(.963)	(.020)	(.000)	
ΔIPI	.533	.101	-.011	.042	0.044	0.460
	(.000)	(.538)	(.012)	(.438)	(.008)	

Note: The table reports the sum of coefficient on the lags of each explanatory variables. The numbers in parentheses are p-values. We determine the number of lags for each regression using AIC and set four as maximum lags. To estimate ΔTBI and ΔEI, we use 2 lags. We use 3 lags and 4 lags to estimate ΔSI and ΔIPI, respectively. We use Newey-West estimator with four lag window.

A ONLINE APPENDIX (to be made available)

A.1 Additional Figures

Figure 10: Correlations: BCI with business investment growth and its components



(a) ΔTBI and BCI

(b) ΔSI and BCI

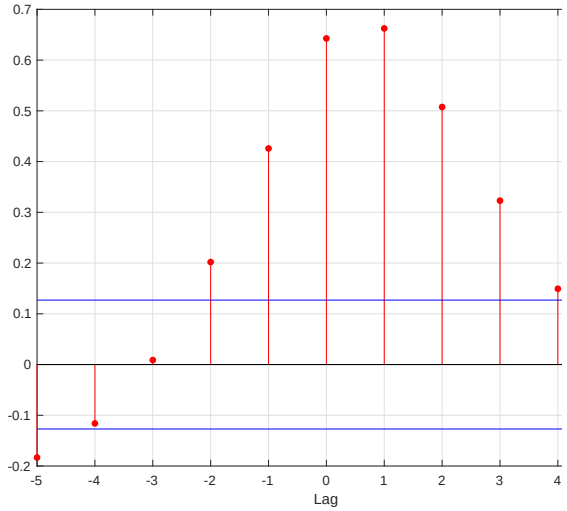
(c) ΔEI and BCI

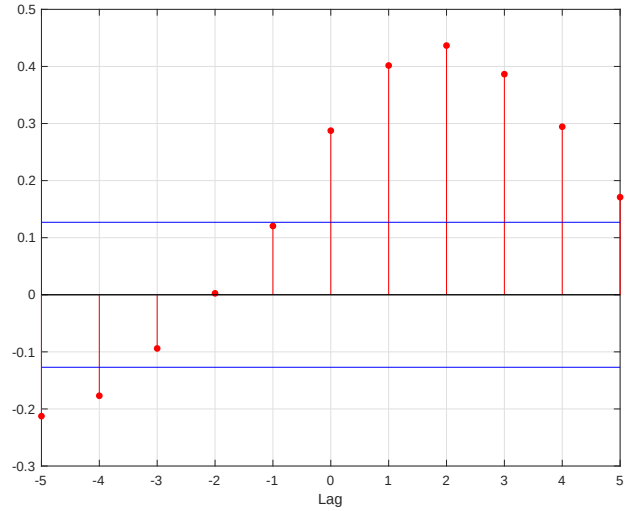
(d) ΔIPI and BCI

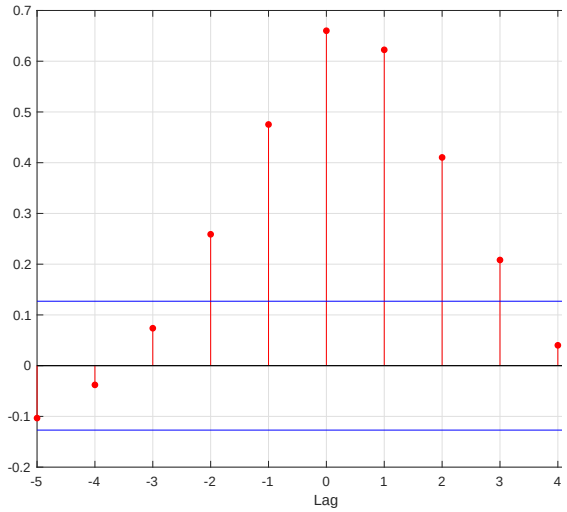
Notes: The NBER recession dates are in grey shading.

Figure 10 shows the relationship between BCI and ΔTBI (and its components) over the period 1955Q1–2016Q4. Panel (a) displays the close movements between ΔTBI and BCI. In particular, there is evidence of a close association during the economic downturns of early 1980s, early 2000s and 2007-2009. Panels (b)–(d) show that all components of investment growth, namely, ΔSI, ΔEI and ΔIPI, are closely related with BCI.

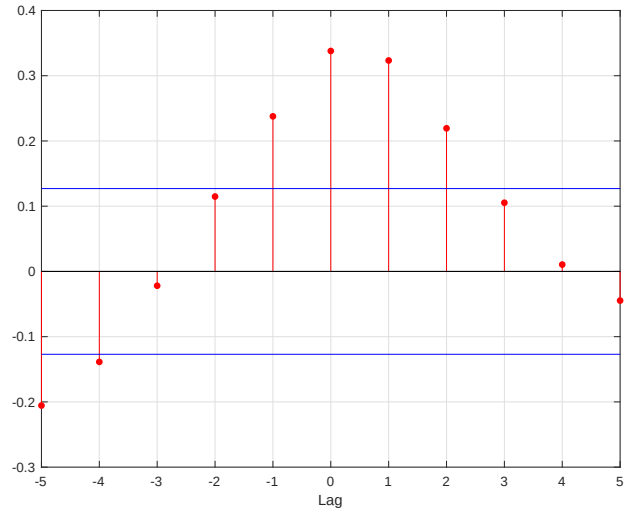
Figure 11: Cross-correlations: BCI with business investment growth and its components







(c) BCI (t) and ΔEI (t+j)



(d) BCI (t) and ΔIPI (t+j)

Note: The blue horizontal lines are the upper and lower confidence bounds in the cross-correlation plot. We use confidence bounds that are two standard errors away from zero.

A.2 Additional Tables

Table 16: Unit root tests

Variables	ADF	PP	Variables	ADF	PP
BCI	-6.007**	-5.997**			
TBI	-0.817	-1.203	ΔTBI	-5.717**	-7.095**
SI	-2.244	-2.398	ΔSI	-6.235**	-10.279**
EI	-0.908	-0.919	ΔEI	-5.896**	-8.748**
IPI	-1.569	-2.385	ΔIPI	-3.376**	-3.872**
GDP	-1.758	-2.053	ΔGDP	-4.617**	-7.875**
CC	-1.302	-1.061	ΔCC	-6.511**	-14.801**
SP	-0.405	-0.550	ΔSP	-11.034**	-14.033**
CF	-1.075	-1.082	ΔCF	-6.693**	-15.989**
TS	-4.215**	-5.008**			
CS	-4.031**	-4.262**			

Note: This table reports test statistics for the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests. We choose the number of lags of the explanatory variable, based on the AIC in the ADF tests and set maximum number of lags to be four. The number of lags in the spectral estimation window in the PP tests is four. The unit root is rejected at 5% and 1% level of significance (denoted by * and **), if the test statistics falls below the corresponding critical value.

Table 17: Bi-variate Granger-causality Wald tests

Explained variables	Explanatory variables	Chi-squared	p-value	Granger-causality
ΔTBI	BCI	73.746	.000	**BCI $\rightarrow$ ΔTBI**
BCI	ΔTBI	2.200	.333	ΔTBI $\not\rightarrow$ BCI
ΔSI	BCI	31.598	.000	**BCI $\rightarrow$ ΔSI**
BCI	ΔSI	1.781	.410	ΔSI $\not\rightarrow$ BCI
ΔEI	BCI	77.989	.000	**BCI $\rightarrow$ ΔEI**
BCI	ΔEI	4.474	.346	ΔEI $\not\rightarrow$ BCI
ΔIPI	BCI	10.304	.036	**BCI $\rightarrow$ ΔIPI**
BCI	ΔIPI	2.701	.609	ΔIPI $\not\rightarrow$ BCI

Note: A variable that Granger-causes another variable is indicated in bold.

Table 18: Multivariate model: Granger-causality Wald tests

Explained variables	Explanatory variables	Chi-squared	p-value	Granger-causality
ΔTBI	BCI	37.313	.000	**BCI $\rightarrow$ ΔTBI**
BCI	ΔTBI	3.096	.213	ΔTBI $\not\rightarrow$ BCI
ΔSI	BCI	13.824	.001	**BCI $\rightarrow$ ΔSI**
BCI	ΔSI	1.361	.506	ΔSI $\not\rightarrow$ BCI
ΔEI	BCI	36.180	.000	**BCI $\rightarrow$ ΔEI**
BCI	ΔEI	3.222	.200	ΔEI $\not\rightarrow$ BCI
ΔIPI	BCI	7.067	.132	BCI $\not\rightarrow$ ΔIPI
BCI	ΔIPI	3.780	.437	ΔIPI $\not\rightarrow$ BCI

Note: A variable that Granger-causes another variable is indicated in bold.

Table 19: OOS results using rolling window method: Predictive ability of BCI for investment growth

Category of investment	R^2_{OS}	p-value
ΔTBI	.092***	.002
ΔSI	.028	.108
ΔEI	.06***	.003
ΔIPI	-.034	.495

Note: The OOS results are based on one-step-ahead forecasts for 1990Q1–2016Q4. A positive R^2_{OS} indicates that the addition of BCI in prediction equation helps forecast the future investment growth. We report the p-value of the Clark and West (2007) statistics corresponding to a test that the null hypothesis of $R^2_{OS} \leq 0$ against $R^2_{OS} > 0$. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.