Three Essays in Macroeconomics with a Focus on Confidence, Investment and the Business Cycle

by

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Abstract

This thesis includes three essays on empirical macroeconomics. The first chapter studies how informative business confidence is for investment growth, 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.

The second chapter explores the hypothesis that consumer confidence drives household investment. We use a survey-based consumer confidence measure in structural VAR analysis to identify a confidence shock. Household investment increases and follows a persistent hump-shaped response after a positive confidence shock. The responses of total hours-worked and output are also highly persistent. Confidence

shocks account for a substantial share of variation in household investment, total hours-worked and output. We show that household investment plays a quantitatively important role in the transmission of confidence shocks in the economy. Our findings suggest that demand side forces originating in consumer's social and psychological factors may be a fruitful direction for studying household investment dynamics and their relationship with the business cycle.

The final chapter studies the effect of profit uncertainty on US manufacturing firms' inventory investment, using an unbalanced panel data for 1981–2017. The main findings are: (i) US firms hold larger stocks of inventories when uncertainty is high; (ii) each component (i.e. raw materials, work-in-progress and finished goods) of inventory investment is positively driven by higher uncertainty; (iii) small firms do not appear to increase inventory investment with higher uncertainty; and (iv) remarkably, high leverage firms increase inventory investment even in the tightened financial constraints. The findings suggest that the firms' characteristics is an important mechanism through which uncertainty affects inventory investment over the business cycle.

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Chapter 1

Does Business Confidence Matter for Investment?

1.1 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 research that has studied consumer confidence or sentiment and its ability to forecast macroeconomic variables. [Leeper \(1992\)](#) finds that consumer sentiment

¹Historically, 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).

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

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 the 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 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

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

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

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 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

⁵Many 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.

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 1.2, we describe the data and preliminaries. In section 1.3, we determine the incremental predictive ability of business confidence for investment growth and its components, using in-sample and OOS data. In section 1.4, we evaluate the OOS forecasting ability of business confidence for investment downturns and direction of investment growth, using a probit forecasting model. In section 1.5, we examine the impulse responses of business investment growth to business confidence innovations. In section 1.6, we present a variety of robustness checks and section 1.7 concludes.

1.2 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 1.1](#) shows the main data used in the analysis and [Table 1.1](#) describes the abbreviation of the list of all the variables.

Table 1.1: List of variables

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
BCI	Business confidence index
TS	Term spread
CS	Credit spread
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

Note: TBI consists of SI, EI and IPI.

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.⁸ 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

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

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

⁸We use a trend to test a unit root for variables in level. However, we do not use trend for the variables in first-difference.

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.

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 variables, 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.

1.3 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.

1.3.1 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:

$$\Delta \log I_t = \alpha_0 + \sum_{i=1}^q \alpha_i \Delta \log I_{t-i} + \sum_{i=1}^q \gamma_i Z_{t-i} + v_t, \quad (1.3.1)$$

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 v_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 \(1995\)](#)).⁹ [Barro \(1990\)](#) uses real stock price as a 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 (1.3.1) to get a BCI-nested model as:

$$\Delta \log I_t = \alpha_0 + \sum_{i=1}^q \alpha_i \Delta \log I_{t-i} + \sum_{i=1}^q \gamma_i Z_{t-i} + \sum_{i=1}^q \beta_i BCI_{t-i} + v_t, \quad (1.3.2)$$

We employ two types of statistical tests to investigate whether BCI has any predictive ability after controlling for other relevant economic variables mentioned above.¹⁰

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, $\beta_i = 0$ ($i = 1, \dots, q$), is rejected if the corresponding

⁹[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 liquidity, where liquidity is retained earnings plus depreciation.

¹⁰Allowing for different lags for different sets of variables in (1.3.2) does not affect our empirical findings (the results are available upon request).

p -value falls below the desired level of significance.

Table 1.2 reports the estimation results from baseline model (1.3.1) and BCI-nested model (1.3.2) 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.¹¹ 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.

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

¹¹We exclude intercept to check the joint performance of control variables. If they are jointly insignificant, the model will be random walk model.

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.

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 (1.3.1) and (1.3.2), adding one quarter at a time to obtain a series of one-step-ahead forecasts.¹² The recursive estimation is more efficient and performs better than rolling window estimation in point forecasting (see [Carriero et al. \(2015\)](#)).¹³ To evaluate the one-step-ahead predictability of BCI for business investment growth, we compute the OOS R^2 (R_{OS}^2), which is calculated as follows:

$$R_{OS}^2 = 1 - (MSFE_i/MSFE_j), \quad (1.3.3)$$

¹²The general set up for obtaining OOS data is similar to [Estrella and Mishkin \(1998\)](#). We obtain out-of-sample data in the following way: We first estimate a given model using data from the beginning of the sample up to 1989Q4. We then use this estimate to generate a one-quarter-ahead forecast for 1990Q1. After adding one quarter to the estimation period, we repeat the procedure over the period 1990Q1 to 2016Q4.

¹³The 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.

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

$$MSFE = P^{-1} \sum_{t=R+1}^T \left(\Delta \log(I_t) - \widehat{\Delta \log(I_t)} \right)^2 \quad (1.3.4)$$

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 (1.3.2) and (1.3.1), respectively. A positive R_{OS}^2 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 $R_{OS}^2 \leq 0$ against $R_{OS}^2 > 0$.

Table 1.3 includes the results of OOS predictive performance of BCI for ΔTBI and its components. It reports the R_{OS}^2 and p -value for the Clark and West (2007) statistics. The R_{OS}^2 captures the improvement in MSFE from the BCI-nested model relative to MSFE from the baseline model. Since the R_{OS}^2 for ΔTBI is 0.052, BCI has OOS predictive ability for future ΔTBI after controlling for other determinants of investment. The null hypothesis of $R_{OS}^2 \leq 0$ against $R_{OS}^2 > 0$ is rejected at the 1% level since the p -value is 0.006. The R_{OS}^2 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_{OS}^2 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:¹⁴

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

where, $\hat{u}_j^2$ and $\hat{u}_i^2$ 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 1.2](#) 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. Additionally, the OOS predictive ability increases in the period following the financial crisis of 2008. Panels (b–d) show the forecasting 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 fore-

¹⁴ [Goyal and Welch \(2003, 2008\)](#) use this approach to show the CDSFE of historical average vs. predictive variable's regression.

casting model exhibits the OOS predictability for ΔTBI and its components (except ΔIPI), more importantly during the financial crisis and the period afterwards.

1.4 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.

1.4.1 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, $d_t, t = 1, 2, \dots, T$ 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:¹⁵

$$d_t = \begin{cases} 1, & \text{if the business investment growth is below the sample average for more than} \\ & \text{two consecutive quarters.} \\ 0, & \text{otherwise.} \end{cases} \quad (1.4.1)$$

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 1.3](#). 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.

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.¹⁶ Let Ω_t be the information set available at time t . Conditional on Ω_{t-1} , d_t has a Bernoulli distribution, $B(\cdot)$, with probability p_t . The conditional probability of investment downturns, $d_t=1$, satisfies:

$$p_t = E_{t-1}(d_t) = P_{t-1}(d_t = 1) = \Phi(\pi_t), \quad (1.4.2)$$

where $E_{t-1}(\cdot)$ and $P_{t-1}(\cdot)$ 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

¹⁵This definition is similar to that used for output downturns in [Taylor and McNabb \(2007\)](#).

¹⁶Previously, 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.

variable for investment downturns using a univariate probit model:¹⁷

$$\pi_t = \omega + \psi X_{t-k}, \quad (1.4.3)$$

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 .

$$\pi_t = \omega + \delta V_{t-k} + \phi \text{BCI}_{t-k}, \quad (1.4.4)$$

where, V_t denotes the vector of control variables.

¹⁷We start from univariate model since more parsimonious static probit model performs better for OOS test (see, for example, [Pönkä \(2017a\)](#)).

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.¹⁸ We use recursive estimation, adding one quarter at a time to obtain a series of k -step-ahead forecasts for the period 1990Q1–2016Q4.¹⁹ We use three forecast evaluation methods. First, we use pseudo R^2 , denoted as $\text{ps.}R^2$, developed by [Estrella \(1998\)](#).²⁰ It is defined as:

$$\text{ps.}R^2 = 1 - (\log L_u / \log L_c)^{-(2/n) \log L_c}, \quad (1.4.5)$$

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 $\text{ps.}R^2$ 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:

$$QPS = P^{-1} \sum_{t=R+1}^T 2 \left(\hat{P}(d_{t+h} = 1) - d_{t+h} \right)^2, \quad (1.4.6)$$

¹⁸We consider dynamic probit model in the robustness section.

¹⁹The results based on the alternative approach of rolling-window estimation are available upon request.

²⁰In probit models, the $\text{ps.}R^2$ 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.

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.

In the presence of the serial correlation usual sampling variance of the score obtained by assuming independence is no longer valid (see, [Lahiri and Yang \(2016\)](#)). 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 1.²¹ The 45° 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:

$$AUC = \int_0^1 ROC(r)dr, \quad (1.4.7)$$

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

²¹[Berge and Jordà \(2011\)](#), [Lahiri and Yang \(2015\)](#) 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.

performance.

Table 1.4 displays the value of $ps.R^2$, QPS and AUC from OOS results for each predictor from equation (1.4.3). 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 1.4, 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 1.5, 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 1.4 and Figure 1.4. 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 (1.4.4) without BCI and with BCI. Table 1.5 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 1.6 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 1.1 (panel F).

1.4.2 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 theoret-

ical 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 $B(\cdot)$ with probability with p_t . The conditional probability of a positive sign of investment growth, $g_t|\zeta_{t-1} = 1$, satisfies:

$$p_t = E_{t-1}(g_t|\zeta_{t-1}) = P_{t-1}(g_t|\zeta_{t-1} = 1) = P_{t-1}(g_t > 0|\zeta_{t-1}) = \Phi(\Pi_t), \quad (1.4.8)$$

where $E_{t-1}(\cdot)$ and $P_{t-1}(\cdot)$ 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:

$$\Pi_t = \varphi + \kappa X_{t-k}. \quad (1.4.9)$$

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

$$\Pi_t = \varphi + \theta C_{t-k} + \vartheta BCI_{t-k}, \quad (1.4.10)$$

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 forecasts 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 1.6](#) reports the values of $ps.R^2$, QPS, AUC and SR for each predictor from (1.4.9). 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 (1.4.10) without BCI and with BCI, respectively. Table 1.7 reports the results. The BCI-nested model has better OOS predictive performance relative to BCI non-nested model over 1–3 quarter forecast horizons.

1.5 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):

$$Y_t = \sum_{i=1}^N A_i Y_{t-i} + \nu_t, \quad (1.5.1)$$

where, $Y_t = [\text{BCI}_t, Z_t, \Delta \log(I_t)]'$ 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, respectively. 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 1.7](#) 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 1.8](#) 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.

1.6 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 1.4.1](#). 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.

1.6.1 Expected growth, interest rate and BCI

We include expected output growth and the interest rate as additional explanatory variables in equation 1.3.1 and 1.3.2 and perform in-sample and OOS tests.²² We construct a predicted value of output growth based on a regression of output growth on its four lags. Table 1.8 and Table 1.9 show the results. Our findings are consistent with previous in-sample and OOS performance results without expected growth and the interest rate.

1.6.2 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 1.11 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 the third month of the quarter for BCI in Table 1.2 (our baseline) is higher than from other approaches of converting monthly to quarterly frequency in Table 1.11.

²²One might argue that BCI may be simply capturing the effect of future output expectations and this expectations may affect both variables, BCI and investment.

1.6.3 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 1.4](#). We then estimate equation (1.4.3) to evaluate the forecasting performance. [Table 1.10](#) 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.

1.6.4 PMI and its components

We also check as a robustness, using PMI as a regressor instead of BCI to estimate total business investment growth.²³ We also use PMI’s components, namely, production/business activity, new orders, employment and supply deliveries, as regressors to estimate the model. [Table 1.12](#) shows the results. The increment of $\bar{R}^2$ is 0.055 and

²³BCI series refers PMI and detail of PMI series is in Appendix. PMI series and its four components, production/business activity, new orders, employment and supplier deliveries, are downloaded from Bloomberg terminal but Inventory component is not available in Bloomberg.

the coefficients of the lags of PMI are jointly significant. This result is consistent with the result from [Table 1.2](#). We also find that these components, production/business activity, new orders and employment have predictive power for total business investment growth controlling for fundamentals since the incremental $\bar{R}^2$ are 0.052, 0.056 and 0.048 of production/business activity, new orders and employment, respectively. However, a supplier deliveries component has quite low incremental $\bar{R}^2$ (i.e. 0.006).

1.6.5 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.²⁴ We make assumptions on what information available at the time of forecast and use three quarter information lags of dependent variable.²⁵ The dynamic probit model is:

$$\pi_t = \omega + \zeta d_{t-k-3} + \delta V_{t-k} + \phi BCI_{t-k}, \quad (1.6.1)$$

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 (1.6.1) without BCI and with BCI. [Table 1.13](#) 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

²⁴[Kauppi and Saikkonen \(2008\)](#), [Nyberg \(2010\)](#), [Pönkä \(2017a\)](#) and among others show dynamic probit model increases the forecasting performances.

²⁵[Nyberg \(2010\)](#) uses nine months lags of the dependent variable (recession indicator) due to the NBER announcement delay.

model.

1.6.6 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 1.9](#) 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 confirms that our results are robust and BCI innovations have important information about future business investment.

1.7 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 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. In addition, we leave real-time vintages excercises for future research since these data can be advantageous in OOS tests (see, for example, [Croushore \(2011\)](#)). Our findings have implications for improving investment forecasts, developing new business cycle models, and studying the role of behavioural factors determining investment growth.

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Figure 1.1: Main data used in the analysis

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 Δ TBI.

Figure 1.2: CDSFE: OOS predictive ability of BCI for investment growth

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 1.3: 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 1.4: 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 1.5: OOS predicted investment downturn 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 downturn probabilities for BCI, TS and ΔSP for 1–4 quarter forecast horizons. The defined downturn dates are in grey shading.

Figure 1.6: 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 1.7: 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 1.8: 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 1.9: 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 1.2: In-sample results: Predictive ability of BCI for investment growth

Category of investment	(a) Baseline		(b) BCI-nested	
	$\bar{R}^2$	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 1.3: OOS results: Predictive ability of BCI for investment growth

Category of investment	R_{OS}^2	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_{OS}^2 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 $R_{OS}^2 \leq 0$ against $R_{OS}^2 > 0$. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 1.4: 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***
Δ SP	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**
Δ GDP	ps. R^2	.182	.179	.142	.085
	QPS	.372	.378	.399	.424
	AUC	.745***	.747***	.710***	.654***
Δ CC	ps. R^2	.127	.063	.017	.028
	QPS	.418	.439	.461	.461
	AUC	.676***	.620**	.434	.404
Δ CF	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 1.5: 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 1.6: 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 1.7: 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 1.8: In-sample results: Predictive ability of BCI for investment growth

Category of investment	(a) Baseline		(b) BCI-nested	
	$\bar{R}^2$	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 1.9: OOS results: Predictive ability of BCI for investment growth

Category of investment	R_{OS}^2	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_{OS}^2 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 $R_{OS}^2 \leq 0$ against $R_{OS}^2 > 0$. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Table 1.10: 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 1.4.1](#). 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 1.11: In-sample results, using different converting approach of monthly to quarterly BCI data: Predictive ability of BCI for investment growth

Category of investment	(a) Baseline	(b) BCI-nested		(c) BCI-nested		(d) BCI-nested	
	$\bar{R}^2$	Incremental $\bar{R}^2$	p -value	Incremental $\bar{R}^2$	p -value	Incremental $\bar{R}^2$	p -value
Δ TBI	.459	.051	.000	.032	.000	.059	.000
Δ SI	.287	.017	.069	.014	.089	.019	.055
Δ EI	.383	.055	.000	.031	.002	.065	.000
Δ IPI	.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 Δ TBI and Δ EI, we use 2 lags. We use 3 lags and 4 lags to estimate Δ SI and Δ IPI, respectively. We use Newey-West estimator with four lag window.

Table 1.12: In-sample results: Predictive ability of PMI and its components for investment growth

Category of investment	PMI	Production	New orders	Employment	Supplier Deliveries
ΔTBI	.055	.052	.056	.048	.006
	(.000)	(.000)	(.000)	(.000)	(.080)

Note: We use PMI as a regressor instead of BCI. We also use PMI's components (regressors), namely, production/business activity, new orders, employment and supply deliveries. We report increment of $\bar{R}^2$ ($\bar{R}^2$ from PMI-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 parentheses. We determine the number of lags for each regression using AIC and set four as maximum lags. To estimate ΔTBI , we use 2 lags. We use Newey-West estimator with four lag window.

Table 1.13: 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 1.14: Baseline forecast of business investment growth

Variables	lags of dependent variable	lags of Δ GDP	lags of Δ CC	lags of Δ CF	lags of Δ SP	$\bar{R}^2$
Δ TBI	.468 (.000)	.508 (.030)	.007 (.513)	.088 (.061)	.099 (.000)	0.459
Δ SI	.261 (.001)	.057 (.005)	.103 (.040)	-.099 (.119)	.115 (.020)	0.287
Δ EI	.352 (.007)	.672 (.055)	.011 (.963)	.181 (.020)	.161 (.000)	0.383
Δ IPI	.533 (.000)	.101 (.538)	-.011 (.012)	.042 (.438)	0.044 (.008)	0.460

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 Δ TBI and Δ EI, we use 2 lags. We use 3 lags and 4 lags to estimate Δ SI and Δ IPI, respectively. We use the Newey-West estimator with four lag window.

Table 1.15: 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 1.16: 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.

Chapter 2

Consumer Confidence and Household Investment

2.1 Introduction

A well-known and robust property of US household investment (residential investment plus consumer durables) is that it leads the business cycle.¹ This fact is quite remarkable because over the past 70 years, a rise or fall in quarterly real Gross Domestic Product (GDP) relative to a long run trend is preceded by a rise or fall in household investment. While this leading indicator property is useful for policy makers for assessing the future direction of the economy, it has been challenging to provide

¹Each component, i.e., residential investment and consumer durables, also displays this property. [Brault and Khan \(2018\)](#) show that unlike the real interest rate and labour productivity, household investment retains its leading indicator property in the post-1985 data. [Leamer \(2008\)](#) has documented that household investment consistently and substantially contributes to the most weakness prior to the recessions whereas eight of the ten recessions were preceded by severe problems in housing in the past fifty years. [Leamer \(2015\)](#) further stresses the importance of housing for the business cycle.

an explanation.² Many recent models proposed in the literature have studied distinct channels within a rational expectations framework (see, for example, [Ren and Yuan \(2014\)](#), [Kydland, Rupert and Šustek \(2016\)](#) and [Khan and Rouillard \(2018\)](#)). It is, however, possible that behavioural factors such as evolving consumer confidence have also played a role in sustaining this property of household investment (possibly either through ‘animal spirits’ reflecting optimism and pessimism over the business cycle or through anticipations about future fundamentals). The objective of this paper is to investigate the empirical support for this hypothesis.

There are three reasons that motivate our focus on consumer confidence. First is that the lead of residential investment over GDP originates exclusively from single family structures and ‘other structures’ but not from multi-family structures.³ The correlations between one quarter ahead cyclical output and current investment in single family structures are the largest in the sample, indicating a one-quarter lead. A similar pattern exists ‘other structures’. In the post-1985 sub-sample, the leading property of ‘other structures’ investment has become even stronger and it leads output by four quarters. Together with consumer durables, these components of household investment may be affected by optimism and pessimism of a family decision-making unit and/or reflect responses to news about future fundamentals that affects confidence contemporaneously. Second is that many empirical studies (discussed below)

²The early literature on home production features studies that do not reproduce the lead in residential investment over the business cycle (see, for example, [Benhabib, Rogerson and Wright \(1991\)](#), [Greenwood and Hercowitz \(1991\)](#), [McGrattan, Rogerson and Wright \(1997\)](#), and [Gomme, Kydland and Rupert \(2001\)](#)).

³The component ‘other structures’ in residential investment consists primarily of manufactured homes, improvements, dormitories, net purchases of used structures, and brokers’ commissions on the sale of residential structures .

have found that consumer confidence has predictive power for a variety of macroeconomic variables. However, to the best of our knowledge, we are first to examine the role of consumer confidence in the context of the leading indicator property of household investment. Third is that there is renewed interest in studying the role of consumer confidence in understanding and interpreting business cycles from a variety of perspectives. [Beaudry, Nam and Wang \(2011\)](#) examine the role optimism and pessimism shocks, estimated using stock price and consumption data, in driving US output and hours over the business cycle. [Barsky and Sims \(2012\)](#) study whether the innovations in consumer confidence reflect ‘animal spirits’ or ‘news about future fundamentals’. [Bachmann and Sims \(2012\)](#) consider the role of confidence in the transmission of government spending shocks during a recession. More recently, [Angeletos, Collard and Dellas \(2018\)](#) study the quantitative role of consumer confidence to interpret the business cycle, and [Hintermaier and Koeniger \(2018\)](#) present a dynamic model with consumer confidence to study how it interacts with household debt to generate the observed fluctuations in house prices and consumption. None of these papers examine the role of confidence for household investment which is our objective.

We use the University of Michigan’s Surveys of Consumers and focus on its Index of Consumer Expectation (ICE) as the measure of consumer confidence in our empirical analysis.⁴ There are three ‘forward-looking’ questions underlying the construction of ICE. These index questions, listed as *Q_2*, *Q_3*, and *Q_4* in the Survey, are as follows:⁵

- *Q_2. Now looking ahead—do you think that a year from now you (and your*

⁴<http://www.sca.isr.umich.edu/>

⁵The other two questions are about current conditions. These are presented in the Appendix.

family living there) will be better off financially, or worse off, or just about the same as now?

- *Q_3. Now turning to business conditions in the country as a whole—do you think that during the next twelve months we’ll have good times financially, or bad times, or what?*
- *Q_4. Looking ahead, which would you say is more likely—that in the country as a whole we’ll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?*

In constructing ICE, first a relative score is computed (the percent giving favourable replies minus the percent giving unfavourable replies, plus 100) for each of the index questions. Then the relative score is rounded to the nearest whole number. And lastly, using the formula shown below, where the sum of the scores is divided by the base-year value of 4.1134, and 2.0 is added as a constant to correct for sample design changes from the 1950s. The ICE is constructed as follows:

$$ICE = \frac{Q_2 + Q_3 + Q_4}{4.1134} + 2.0$$

A crucial first step in our empirical analysis is to determine if consumer confidence leads household investment. The answer to this question is a crucial first step for our hypothesis because if it does not, then consumer confidence cannot be a potential driver of household investment. We proceed in the standard way (see, for example, [Kydland and Prescott \(1990\)](#) and [Cooley and Prescott \(1995\)](#)) and compute cross-

correlations between ICE and the cyclical component of household investment, and define the lead based on the largest cross-correlation (including contemporaneous correlation) in absolute terms. Specifically, we take the natural log of household investment and de-trend with HP-filter (using a smoothing parameter of $\lambda = 1600$).⁶ Since ICE is stationary, we do not de-trend it.

We find that ICE leads household investment by two quarters over the sample period 1960Q1-2017Q4. This means that when consumer confidence is high, household investment will be high in the near future, followed by business investment, output, and hours. In addition, we find that ICE Granger-causes household investment but the reverse causality is not present in the data. This suggests that movements in ICE contain information that can help predict future household investment.

Next, we conduct a Vector Autoregression (VAR)-based analysis to evaluate the impulse responses of household investment to a one-standard deviation ICE shock. As a baseline, we consider a four-variable VAR that includes ICE (ordered first), household investment, hours-worked, and output, and use Cholesky decomposition to identify the ICE shock. We find that household investment, hours-worked, and output all increase following the ICE shock. These impact responses are statistically different from zero. The effects on all the three variables build up over time. Both household investment and hours-worked have a hump-shaped response, with the peak responses occurring between one to two years after the shock. The responses are highly persistent, in particular, that of output and are all statistically significant. Variance decomposition results show that confidence shocks account for a substan-

⁶Using the recently proposed filter in [Hamilton \(2017\)](#) produces similar results.

tial share of variation in household investment, total hours-worked and output. In particular, confidence shocks account for 46, 38, and 74 percent of the forecast error variance of household investment, total hours worked and output at 40 quarter horizon. Remarkably, the correlations based on historical decomposition conditional on ICE shock only show that confidence leads household investment.

What role does household investment play in transmitting confidence shocks to the broader economy? To answer this important question, we apply the methodology used in [Bernanke et al. \(1997\)](#), [Sims and Zha \(2006\)](#), [Kilian and Lewis \(2011\)](#), and [Bachmann and Sims \(2012\)](#). We construct a hypothetical impulse response of the output to confidence shock, holding household investment fixed at all forecast horizons. We find that the response of output is lower in all horizons when household investment is forced to not respond to the confidence shock relative to when it is left unconstrained. This finding suggest that consumer confidence influences household investment dynamics which then get transmitted to future movements in output.

We find that confidence shocks do not appear to be related to movements in current or future total factor productivity and relative price of investment. These findings suggest that demand side forces originating in consumer’s social and psychological factors may be a fruitful direction for studying household investment dynamics and their relationship with the business cycle.

The rest of the paper is organized as follows. In section [2.2](#) we present the related literature with our paper. In section [2.3](#), we provide the construction and sources of the data, the cross-correlations and Granger-causality between the variables. In section [2.4](#), we discuss the empirical results of ICE shocks over business cycles. In

section 2.5, we present a variety of robustness checks and section 2.6 concludes.

2.2 Related literature

Our paper is related to previous research that examined the lead of household (and residential) investment over output. That literature, however, did not investigate consumer optimism and pessimism as drivers of household investment. [Kydland, Rupert and Šustek \(2016\)](#) study the dynamic behaviour of the US residential investment. They build a model showing that the cyclical properties of long term fixed rate mortgage loans can explain the fact that residential investment leads the business cycle in the US and coincident movement in European countries. [Khan and Rouillard \(2018\)](#) find that severeness of home-owners' borrowing constraints drive the lead of residential investment over output in a multi-agent model. [Ren and Yuan \(2014\)](#) use a dynamic stochastic partial equilibrium model with Total Factor Productivity (TFP) news shocks, collateral constraints and agent heterogeneity to explain the lead of residential investment over output. These recent studies are within the standard rational expectations framework. By contrast, in this paper we explore the role of consumer's beliefs or attitudes as potential drivers of the household investment dynamics over the business cycle. Our analysis is empirical as we are interested in determining whether or not consumer confidence can play a driving role for household investment dynamics.

A large body of the literature studies whether the consumer confidence has the ability to forecast the macroeconomic variables, such as output, consumer spending,

employment and productions. In early work on the predictive value of consumer attitudes or sentiments, [Tobin \(1959\)](#), [Adams \(1964\)](#) and [Friend and Adams \(1964\)](#) estimated consumption functions and found mixed results. Relatedly, [Fuhrer \(1993\)](#), [Carroll, Fuhrer and Wilcox \(1994\)](#) , [Bram and Ludvigson \(1998\)](#), [Ludvigson \(2004\)](#) and [Cotsomitis and Kwan \(2006\)](#) find that lagged consumer confidence has some explanatory power for current changes in household spending after using control variables. [Lahiri, Monokroussos and Zhao \(2016\)](#) use real time data and find evidence that consumer confidence helps in predicting household expenditures. Moreover, [Matusaka and Sbordone \(1995\)](#) use a VAR specification to assess the Granger-causality between consumer confidence and economic fluctuations after controlling for economic fundamentals and find that the consumer confidence Granger-causes gross national product. On the other hand, [Leeper \(1992\)](#) studies the role of consumer attitudes in forecasting economic activities and finds that attitudes do not improve the forecasting accuracy of production and unemployment when financial variables, stock market price and short term interest rate, are taken into account. [Throop \(1992\)](#) establishes that consumer sentiment is a significant determinant of household's purchases of durable goods. In this paper we study how the consumer sentiment shock affect not only durable goods but, importantly, residential investment. In addition, our focus is on business cycle dynamics of household investment.

[Aastveity, Anundsen and Herstad \(2017\)](#) find that residential investment is useful in predicting recessions, using both in-sample and out-of-sample tests for 12 Organization for Economic Co-operation and Development (OECD) countries. However, the paper does not consider the role of consumer confidence as a precursor to business

cycle movements in residential investment as we do.

[Barsky and Sims \(2012\)](#) assess the response of macroeconomic aggregates to an exogenous shift in consumer confidence shocks, using a trivariate VAR model. They find that surprise changes in consumer confidence are associated with long-lasting movements in output and consumption of (non-durable) goods and services.⁷ The impulse responses of consumption and output to one-standard consumer confidence innovations are hump-shaped and permanent. Our focus, by contrast, is on household investment. [Bachmann and Sims \(2012\)](#) study the role of confidence in the transmission of fiscal policy change. They find that confidence is part of the transmission of government spending shocks during recessions. Our focus is on household investment in the transmission of consumer confidence shock rather than transmission of fiscal policy changes. Finally, [Angeletos, Collard and Dellas \(2018\)](#) study the quantitative role of confidence for the business cycle. They introduce the notions of optimism and pessimism as confidence shocks which capture the gap between first- and the higher-order beliefs of model-based TFP. By contrast, we use a survey-based measure of confidence to study the drivers of household investment dynamics.

⁷They mainly focus on non-durable goods and mention that the response of consumer durables is similar. By contrast, our focus is on household investment which includes consumer durables.

2.3 Data and preliminaries

2.3.1 Data

Our data span the period 1960Q1–2017Q4. We use National Income and Product Accounts (NIPA) Table 1.1.3 of the Bureau of Economic Analysis (BEA) to obtain the quantity series of real gross domestic product (GDP), personal consumption expenditures on durable goods, residential investment, non-residential investment and government consumption expenditure. We obtain total population from NIPA Table 7.1. The housing starts series (Housing Starts: Total: New Privately Owned Housing Units Started), total hours worked, unemployment rate, durable goods (industrial production), 10-year government bond rate and 3-month treasury bill rate are from the FRED database of the Federal Reserve Bank of St. Louis. We use NIPA Table 1.1.4 to obtain price indices of durable goods, residential investment, equipment investment and GDP. We use the federal funds rate as measure of the nominal interest rate, and estimated the nominal interest rate when the zero lower bound is not binding. When it is binding, we use the estimates for nominal interest rates from from [Wu and Xia \(2016\)](#). The utilization-adjusted series on TFP growth is from [Fernald \(2014\)](#) and we convert it to a log level series. The stock return is the log difference of real S&P composite stock price index and we obtain the index from Robert Shiller’s webpage.⁸ We define Relative Price Investment (RPI) as the equipment investment price index divided by the GDP price index.

⁸<http://www.econ.yale.edu/shiller/>

We define household investment as the sum of residential investment and consumption expenditures on durable goods. We provide the details of the household investment construction in the Appendix. We normalize all of these variables by the population. The consumer confidence data is from the University of Michigan’s Surveys of Consumers. The Appendix provides the details of the survey questions. We mainly focus on the ICE. Finally, we obtain the business confidence index from the OECD database.

In [Figure 2.1](#), we plot the quarterly series of ICE and household investment for the period 1960Q1–2017Q4. The household investment has an overall upward trend with decreases occurring around the NBER recession dates. In particular, household investment decreases heavily during the Great Recession of 2007–2009. It is evident from the figure that all the recessions are preceded by a fall in ICE. Notably, all the major falls in ICE are followed by large decreases in household investment which precede the recessions. In [Figure 2.2](#), we show the quarterly series of residential investment, durable goods, housing starts, output, business investment (private non-residential fixed investment) and total hours worked for the period 1960Q1–2017Q4 in Panels (a)–(f), respectively.

2.3.2 Does consumer confidence lead household investment?

[Figure 2.3](#) shows the cross-correlation of ICE with macroeconomics variables at various leads and lags (i.e. $Corr(ICE_t, X_{t+j})$ for $j = \pm 5, 4, 3, 2, 1, 0$) for the period 1960Q1–2017Q4. Panel (a) shows that ICE is positively correlated with future house-

hold investment (HI). The largest correlation (0.33) between ICE at t and HI is at $t + 2$, which implies that ICE leads household investment by two quarters. Panel (b) shows the cross-correlations between ICE and housing starts. We find that ICE leads housing starts by one quarter. The leading property of ICE over household investment and housing starts is a clear evidence in support of the hypothesis that consumer confidence can potentially influence household investment. We investigate this in more detail in the subsequent sections. With this established, panels (c) and (e) confirm that ICE also leads two key macroeconomic variables, namely, output, total hours worked, and business investment. ICE leads output and hours by four quarters and business investment by five quarters. Finally, in Panel (d), we show the cross-correlations of ICE and the business confidence index. There is no lead and lag pattern between these two confidence indices since the contemporaneous correlation is the largest.

2.3.3 Does consumer confidence Granger-cause household investment?

We perform Granger causality tests to check whether or not ICE Granger-causes household investment. We take the natural log for all the variables and use the Akaike Information Criteria (AIC) to choose the lag length of the variables. [Table 2.1](#) shows the results of Granger causality tests using a bivariate VAR model. The null hypothesis that ICE does not Granger cause household investment is rejected since the associated p -value is 0.001. Moreover, the hypothesis of reverse causality is rejected.

That is, household investment does not Granger cause ICE. The bi-variate Granger causality tests also show that ICE Granger-causes total hours worked and output but not vice-versa. We also check whether ICE Granger-causes the components of household investment (i.e. residential investment and durable goods). We find that ICE Granger-causes residential investment and durable goods, but conversely, these components of household investment do not Granger-cause ICE in a bi-variate VAR framework. These findings suggest that consumer confidence contains information that can help predict household investment and other macroeconomic variables.

2.4 VAR analysis

In this section, we assess the macroeconomic effects of ICE shocks—the exogenous shifts in consumer confidence—using a VAR framework. A key difference relative to the previous literature on confidence shocks is that our main variable of interest is household investment. Since we are interested to see how changes in ICE can propagate to the economy through the household investment channel, we also include hours worked and real GDP in our analysis.

2.4.1 The effects of consumer confidence shocks

In the baseline case, we consider a four-variable VAR with ICE, household investment, total hours worked and real output.⁹ All four variables enter the VAR in log-levels

⁹Total hours worked and output are good indicators of the business cycle.

with four lags.¹⁰ We use AIC to choose the lag length. Given our findings in the previous section, we order ICE first in the VAR and use the Cholesky orthogonalization to identify the ICE shock.

Figure 2.4 shows the impulse responses to an ICE shock. The shaded areas are one-standard-error confidence bands based on the Kilian (1998) bias-corrected bootstrap after bootstrap procedure. A one standard deviation positive ICE shock has a positive impact on household investment, total hours worked and output. These effects are statistically significant at 5 percent level. The impact effects are followed by hump-shaped and highly persistent responses of these variables. The peak response of household investment to a one standard deviation ICE shock is 2.2 percent. The peak responses of output and total hours worked are 0.8 percent and 0.75 percent, respectively. The responses of household investment and output are very persistent; at a horizon of 40 quarters, they are statistically significant at a 5 percent level and over 0.7 percent. The size of the response of hours worked for the same horizon is not as high, yet it is also statistically significant at a 5 percent level.

Barsky and Sims (2012) examine the response of non-durable consumption and real output to a confidence shock (using the confidence measure based on sub-question Q4 in ICE denoted as E5Y) in a three-variable VAR. They showed that the consumer confidence has powerful predictive implications for the future paths of macroeconomic variables. The impulse responses of consumption and output to a one standard consumer confidence innovations are gradually increasing and statistically significant,

¹⁰We follow the common practice in the literature of putting variables in levels in the VAR. First differencing may lose information and it produces no gain in asymptotic efficiency in an autoregression process (see, Fuller (1976)).

and remain positive in the long run. Although our variables, except for output, are different from theirs, the response of output is quantitatively similar.

To consider the possibility that our confidence measure may contain information already contained in other variables in the VAR, we put ICE last in the VAR system. [Figure 2.5](#) displays the impulse responses to one-standard-deviation innovation to ICE for this orthogonalization. The impulse responses of household investment, total hours worked and output to ICE innovation are not significantly different from reordering the variables in the VAR system. In this case, a positive shock to ICE does not have an impact on household investment, total hours worked and output by construction since ICE is ordered last in the VAR. However, a one standard deviation ICE shock still produces a hump-shaped pattern and highly persistent responses of household investment, total hours worked and output. The responses of household investment and output to a one-standard-deviation innovation are nearly 0.6 percent at the 40 quarter horizon, and remain statistically significant. These responses are slightly smaller than in the case when ICE is ordered first.

[Figure 2.6](#) displays the variance decompositions of ICE, household investment and output to an ICE shock from both orderings—ICE at first and last—in the VAR system. When ICE is ordered first in the VAR, the ICE innovations account for around 46, 38, and 74 percent of the forecast error variance of household investment, total hours worked and output at 40 quarter horizons, respectively. When ICE is ordered last in the VAR, the ICE innovations account for 28, 20, and 43 percent, respectively. ICE innovations account for 78 percent and 75 percent of their own forecast error variance, ordering ICE first and last, respectively. Note that the variation in ICE is

mostly due to its own innovation, which is consistent with our finding that household investment, total hours worked and output do not Granger-cause ICE.¹¹

2.4.2 Household investment as a business cycle transmission channel

What role does household investment play in the transmission of confidence shocks over the business cycle? To answer this question, we follow the approach developed in [Bernanke et al. \(1997\)](#) and [Sims and Zha \(2006\)](#) and used in [Kilian and Lewis \(2011\)](#), and [Bachmann and Sims \(2012\)](#).¹² Specifically, we consider a hypothetical impulse response of the output to ICE shock, holding household investment fixed at all forecast horizons. Comparing the hypothetical impulse response and actual response of output to confidence shocks provides a measure of how the response of household investment contributes to the propagation of the ICE shock.

Our exposition of the approach below closely follows [Bachmann and Sims \(2012\)](#). We consider the following structural VAR(p) representation (with the constant term suppressed for notational convenience):

$$A_0 Y_t = \sum_{j=1}^p A_j Y_{t-j} + \varepsilon_t, \quad (2.4.1)$$

¹¹We also consider a different measure of confidence, namely, the Index of Consumer Sentiment (ICS) instead of ICE in the same four variable VAR system. There are no significant differences in the responses of household investment, total hours worked and output across the two innovations. This finding suggests that information content of $Q1$ and $Q5$ in the Surveys of Consumers has little effect on macroeconomic variables.

¹²[Bernanke et al. \(1997\)](#), [Sims and Zha \(2006\)](#) and [Kilian and Lewis \(2011\)](#) use this approach of decomposition to shed light on the transmission of monetary policy. [Bachmann and Sims \(2012\)](#) use this approach to understand the role of consumer confidence in the transmission of government shocks.

where, Y_t is $k \times 1$ vector that contains four variables, namely ICE, household investment, total hours worked and output, A_j is $k \times k$ matrix that includes the autoregressive coefficients, p is the number of lags of the variables and j identifies the order of the lag. Finally, the $k \times 1$ vector ε_t denotes the mutually uncorrelated structural shocks and the A_0 is the $k \times k$ lower triangular impact matrix.

We express the above model in a reduced form as:

$$Y_t = \sum_{j=1}^p A_0^{-1} A_j Y_{t-j} + u_t, \quad (2.4.2)$$

where the reduced-form shocks, $u_t = A_0^{-1} \varepsilon_t$, and ε_{1t} , ε_{2t} , ε_{3t} and ε_{4t} are the structural ICE shock, household investment shock, total hours worked shock and output shock, respectively. The vector of structural shocks, ε_t , is a zero mean white noise process with covariance matrix $E(\varepsilon_t \varepsilon_t') \equiv \Omega_\varepsilon = I_k$ such that the reduced-form shocks covariance matrix is $E(u_t u_t') \equiv \Omega_u = A_0^{-1} A_0^{-1'}$.

We impose restrictions on the impact matrix A_0 in order to uniquely recover the structural VAR as follows:

$$A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{2,1} & 1 & 0 & 0 \\ a_{3,1} & a_{3,2} & 1 & 0 \\ a_{4,1} & a_{4,2} & a_{4,3} & 1 \end{bmatrix}_{(k \times k)}.$$

We order ICE first, then household investment, total hours worked and output. We employ a Cholesky factorization of the variance-covariance matrix of reduced-form

innovations, Ω_u , to implement the identification assumption. Our assumption is that household investment, total hours worked and output react contemporaneously to the ICE shocks, whereas ICE does not react on impact to other shocks in the system. The assumption is valid since household investment leads output and ICE leads household investment, total hours worked and output.

Constrained impulse responses: What role does household investment play in the transmission of confidence shocks? To answer this question we follow [Bachmann and Sims \(2012\)](#) and consider a hypothetical scenario of a where the response of household investment to an ICE shock is constrained to be exactly zero for all horizons. To frame the discussion, it is convenient to consider the companion matrix VAR(1) representation of the VAR(p) process.

$$Z_t = \Lambda Z_{t-1} + U_t, \quad (2.4.3)$$

where,

$$Z_t = \begin{bmatrix} Y_t \\ Y_{t-1} \\ . \\ . \\ Y_{t-p+1} \end{bmatrix}_{(kp \times 1)}, \quad \Lambda = \begin{bmatrix} A_0^{-1}A_1 & A_0^{-1}A_2 & \cdots & \cdots & A_0^{-1}A_p \\ I & 0 & 0 & \cdots & 0 \\ 0 & I & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & \cdots & I & 0 \end{bmatrix}_{(kp \times kp)}, \quad \text{and} \quad U_t = \begin{bmatrix} u_t \\ u_{t-1} \\ . \\ . \\ u_{t-p+1} \end{bmatrix}_{(kp \times 1)}.$$

Let $A_0^{-1}(q)$ be the q th column of A_0^{-1} . The impulse response of variable i to

structural shock q at horizon $h = 1, \dots, H$ is:

$$\Phi_{i,q,h} = e_i \Lambda^{h-1} A_0^{-1}(q) \quad (2.4.4)$$

where, e_i is a selection vector of dimension $1 \times k$, with a one in the i^{th} place and zeros elsewhere. Since our objective is to hold fixed the response of household investment to confidence shocks in the system, we set $\Phi_{2,1,h} = 0$ at each forecast horizon, where the position indicators 2 and 1 denote for household investment and confidence shocks, respectively. We then create a hypothetical sequence of household investment shocks, $\varepsilon_{2,h}$, so that we can shut down at each forecast horizon. For this process, we calculate a unit household investment shock on impact, $\varepsilon_{2,1} = a_{2,1}$. We can write this in the following matrix form:

$$A_0^{-1}(2, 1) + A_0^{-1}(2, 2)\varepsilon_{2,1} = 0, \quad (2.4.5)$$

which implies

$$\varepsilon_{2,1} = -\frac{A_0^{-1}(2, 1)}{A_0^{-1}(2, 2)}. \quad (2.4.6)$$

We then calculate the required household investment shocks for subsequent horizons as follows:

$$\varepsilon_{2,h} = -\frac{\Phi_{2,1,h} + \sum_{j=1}^{h-1} e_2 \Lambda^{h-j} A_0^{-1}(2) \varepsilon_{2,j}}{e_2 A_0^{-1}(2)}, h = 2, \dots, H. \quad (2.4.7)$$

Now we use the above household investment shocks series to get the constrained or

hypothetical impulse responses of the variables to ICE shocks. These are:

$$\tilde{\Phi}_{i,1,h} = \Phi_{i,1,h} + \sum_{j=1}^h e_i \Lambda^{h-j} A_0^{-1}(2) \varepsilon_{2,j}, i = 1, \dots, k. \quad (2.4.8)$$

Results

Figure 2.7 shows the impulse responses of ICE, household investment, total hours worked and output to an ICE shock. The blue solid lines and the red dashed lines in the figure show the actual and hypothetical impulse responses, respectively. Shutting down the response of household investment at all horizons has significant effects on the other variables in the VAR system. The response of output to confidence shocks without household investment is substantially attenuated and consistently lower than in the presence of the household investment channel at all horizons. The responses of output to a one-standard-deviation ICE innovation drops to nearly 0.2 percent from 1.4 percent at 40 quarter horizon when we fixed the responses of household investment at zero for all horizons. The responses of total hours worked to ICE shocks is small on impact when the household investment effects are absent. It also subsequently drops at longer horizons without household investment. These results demonstrate that household investment plays a significant role in transmitting confidence shocks to the broader economy.¹³

¹³We also replaced output by business investment in the same structural VAR framework and order ICE, household investment, total hours worked and business investment. The reason for including business investment in VAR is that US household investment leads business investment over the cycle (Fisher (2007)). Figure 2.8 shows the actual and hypothetical impulse response of household investment, total hours worked and business investment. The actual response of household investment, total hours worked and business investment to ICE shock are positive and statistically significant at long horizons. The hypothetical impulse response of total hours worked and business investment are lower than the unconstrained responses. This evidence indicates that household investment dynam-

Finally, we consider a VAR with six variables (ICE, household investment, business investment, government expenditures, total hours worked, and output). We include government expenditures in the VAR as in [Bachmann and Sims \(2012\)](#). [Figure 2.9](#) shows the impulse responses of ICE, household investment, business investment, government expenditure, total hours worked and output. Even when we add business investment and government expenditures in the VAR, the results are consistent with our baseline four-variable VAR. The response of household investment to an ICE shock is positive and statistically significant for short and long horizons. The impulse responses of business investment, total hours worked, and output to ICE shocks also have a positive and significant impact. Government spending, however, does not react to ICE innovation in the beginning but only after a few quarters and is statistically significant at longer horizons. The figure also shows the constrained responses when we mute the responses of household investment to confidence shocks in structural VAR system for all forecast horizons. The constrained responses of business investment, total hours worked and output are lower than unconstrained responses for all forecast horizons.

2.4.3 Historical decomposition

We compute the historical forecast error decomposition to examine the cumulative effect of a confidence structural shock on other variables over time. Specifically, we quantify how much a confidence shock explains of historically observed fluctuations

ics influence business investment dynamics following a confidence shock, hence suggesting that the lagging property of business investment may be driven by how consumer confidence affects household investment.

in household investment, hours worked and output in the VAR system. [Figure 2.10](#) shows the historical decomposition in VAR system with four variables, ICE, household investment, hours worked and output. Panel (a) shows that ICE forecast error variance accounts for ICE innovations for the most of the sample period. Panel (b) displays the historical decomposition of ICE shocks and other fundamentals for the forecast error variance of household investment. Confidence shocks play a small role compared to other fundamental shocks. However, their contribution is substantially higher in the 1990–2002 period. Panel (c) and (d) show the historical decomposition for the forecast error variance of total hours worked and output, respectively. The confidence shocks has little effect for total hours worked forecast error variance. However, the confidence innovations plays a role significantly for output forecast error variance for most of the sample period.

We examine the cross-correlation of household investment with output and hours worked conditional on consumer confidence shocks in VAR framework. [Table 2.2](#) shows the cross correlation (i.e. $Corr(HI_t, X_{t+j}|ICE^{shocks})$ for $j = \pm 4, 3, 2, 1, 0$) results. The conditional correlation between household investment and output is strongly positive. Household investment leads output on conditional confidence shocks by two quarters. The result is consistent with unconditional cross correlations between the two variables. We also find that household investment leads total hours worked conditional on confidence shocks by two quarters.

2.5 Robustness checks

We conduct a variety of robustness checks. These checks consider additional variables in the VAR, sub-samples, and robustness of the transmission channel.

2.5.1 Additional variables in the VAR

We now add nominal interest rate in the baseline VAR to examine the response of household investment and output to confidence shocks in the presence of monetary policy effects. These are shown in [Figure 2.11](#). The responses of household investment, total hours worked and output to one standard deviation consumer confidence shocks are positive on impact and their responses are hump-shaped, and are statistically significant. [Figure 2.12](#) shows the forecast error variance decomposition of confidence shocks. ICE shocks account for about 31, 27, and 46 percent of the forecast error variance of household investment, total hours worked and output at 40 quarter horizons, respectively. Although the contribution of ICE innovations is slightly smaller, our main results are robust to the presence of monetary policy.

Moreover, we perform a VAR analysis with eight variables: stock return, ICE, nominal interest rate, TFP, RPI, household investment, hours worked and output, to control financial and technology related shocks. [Figures 2.13](#) and [2.14](#) show the impulse responses and forecast error variance decomposition to consumer confidence shocks, respectively. The responses of household investment, hours worked and output to exogenous consumer confidence shock are consistent with the baseline VAR

analysis, after controlling for the financial and technology related variables. The contribution of ICE shocks to the forecast error variance of household investment, hours worked and output are qualitatively similar with the baseline VAR model. We have also used term spread instead of stock return with same eight-variables VAR.¹⁴ Figure 2.15 shows the impulse responses to consumer confidence shocks. The responses of household investment, hours worked and output to exogenous consumer confidence shock are consistent with the baseline VAR analysis.

We further check whether the confidence innovations are related to technology variables. To do this, we regress ICE residuals on lagged value of TFP growth and lagged value of RPI growth. Table 2.3 shows the results. We find that the coefficients of TFP growth and RPI growth are not statistically significant with a low R^2 value of 0.008. In addition, we estimate ICE residuals on fourth lagged of TFP and RPI growth and find that the coefficients of TFP growth and RPI growth are not statistically significant with a very low R^2 (i.e. 0.003). Since technology growth variables are not related to the confidence shocks, that indicates that the ICE shocks are not related to current movements in supply-side forces.

2.5.2 Post-1985 period

We check the robustness of our findings to the post-1985 period widely associated with the onset of the Great Moderation period that lasted until 2007. Figures 2.16 and 2.17 show the impulse responses to ICE shocks in the baseline VAR model, ordering

¹⁴The term spread is the difference between the monthly rate of 10-year government bond minus the monthly rate of 3-month treasury bill.

ICE first and last, respectively. The forecast error variance decomposition for ICE shocks are in [Figure 2.18](#). Our baseline findings do not change in any significant manner.

2.5.3 Additional check for the household investment channel

We replace hours worked with the unemployment rate as an alternative measure to capture the cyclicalities in the labour market to analyze whether household investment plays a role in the transmission of consumer confidence over the business cycle. We employ the same procedure as in [section 2.4.2](#), i.e., holding fixed the responses of household investment to consumer confidence shocks at all forecast horizons.

[Figure 2.19](#) presents the IRFs from a four-variables structural VAR with ICE (ordered first), household investment, unemployment rate and output. The blue solid lines and the red dashed lines correspond to the actual and hypothetical impulse responses, respectively. The actual response of the unemployment rate to a one-standard-deviation consumer confidence innovation is negative on impact and followed by a hump-shaped response, and is statistically significant. The response of the unemployment rate to confidence shocks without the household investment channel is substantially muted and consistently lower than the actual response at all forecast horizons. The responses of output to an ICE shock fall from 0.8 percent to 0.4 percent at their peak impact when we force the responses of household investment at zero for all horizons. These results are consistent with those in [section 2.4.2](#), where we use hours worked and output as business cycle measures. They suggest that household

investment plays a significant role in the transmission of confidence shocks over the business cycle.

In order to underline the household investment channel, we estimate the baseline VAR model with four variables, and we shut down the responses of hours worked, instead of household investment. [Figure 2.20](#) shows the results. The actual and hypothetical response of output to ICE shocks are qualitatively same. It implies that hours worked do not transmit consumer confidence shocks to the broader economy in the way that household investment does.

2.5.4 Components of household investment

We now investigate the response of both components (i.e. residential investment and durable goods) of household investment to consumer confidence shocks and their role in the transmission of consumer confidence shocks. There are two advantages for conducting a separate evaluation. The first is analyzing the responses of both variables to consumer confidence shocks. Second, we analyze whether only one or both variables is playing a role in the transmission of consumer confidence to the economy.

We show the results from a four-variables structural VAR framework with ICE, residential investment, hours worked and output, in [Figure 2.21](#). An ICE shock has a positive impact effect on residential investment and is statistically significant. The effect is followed by a hump-shaped response. The peak response of residential investment to a one standard deviation ICE shock is about 2.5 percent increase and at

a 40 quarter horizon is 0.7 percent. The responses of total hours worked and output to ICE shocks is lower on impact and declines at all forecast horizons when residential investment effects are muted. These results suggest that residential investment, which is a key component of household investment, plays a crucial role in transmitting the confidence shocks to the broader economy.

Figure 2.22 shows the results from four-variables structural VAR framework with ICE, durable goods, hours worked and output. The response of durable goods is positive on impact and followed by hump-shaped response. The response is highly persistent and statistically significant. The peak response to a one standard deviation ICE shock is about 2.2 percent increase and 1.4 percent at 40 quarter horizons. The constrained responses of hours worked and output to ICE shocks are lower on impact and also subsequently drops at all horizons than the unconstrained responses. The findings suggest that each component of household investment has positive response to ICE shock and plays a role significantly in the transmission of the ICE shocks over the business cycle.

2.5.5 Possible sub-channel

A plausible story underlying our finding that household investment plays a significant role in transmitting confidence shocks to economy goes as follows: a positive confidence shock leads to more spending in houses and durable goods; then house builders and consumer durables firms react by investing (producing) more houses and durable goods. According to this story, investing more on private capital structure boosts

GDP.

We estimate a five-variables structural VAR with ICE, durable goods(consumption), durable goods (industrial production), hours worked and output. [Figure 2.23](#) shows the results for the period 1985–2017. The direct responses of durable goods, durable goods (industrial production) hours worked and output, when the response of durable goods to ICE shocks is fixed, are lower than the indirect responses of durable goods, durable goods (industrial production) hours worked and output at all horizons. These findings support our confidence shocks transmission story.

2.6 Conclusion

The well known and robust leading indicator property of household investment (consumer durables plus residential investment) has been a challenging business cycle fact to explain. Since single-family homes are the main source of this property for residential investment, it suggests that household investment is likely affected by shifts in consumer confidence at a family decision-making unit level. So far there has been no attempt to connect consumer confidence as source of the leading indicator property. Our paper fills this gap. We use quarterly aggregate data since 1960 and measure consumer confidence from the University of Michigan Surveys of Consumers. We show that consumer confidence leads household investment by two quarters and housing starts by one quarter. Household investment rises persistently in a hump-shaped manner after positive consumer confidence shock. Both hours-worked and output also increase on impact and the effects are highly persistent. The confidence shocks

account for over 40 percent of the variation in household investment over long horizons (40 quarters). These shocks account for a substantial variation in output (nearly 75 percent of all GDP variation) and about 40 percent of the hours variation. We find that household investment plays a quantitatively important role in the transmission of confidence shocks to the economy. Moreover, confidence shocks do not appear to be related to movements in current or future total factor productivity and relative price of investment. Our findings, therefore, suggest that demand side forces originating in consumer's social and psychological factors may be a fruitful direction for studying household investment dynamics and their relationship with the business cycle.

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Table 2.1: Bi-variate model: Granger-causality Wald tests

Explained variables	Explanatory variables	Chi-squared	<i>p</i> -value	Granger-causality
Household investment	ICE	11.000	0.012	ICE → Household investment
ICE	Household investment	5.704	0.127	Household investment $\nrightarrow$ ICE
Residential investment	ICE	11.474	0.003	ICE → Residential investment
ICE	Residential investment	3.603	0.165	Residential investment $\nrightarrow$ ICE
Durable goods	ICE	22.416	0.000	ICE → Durable goods
ICE	Durable goods	3.065	0.216	Durable goods $\nrightarrow$ ICE
Business investment	ICE	11.474	0.003	ICE → Business investment
ICE	Business investment	3.603	0.165	Business investment $\nrightarrow$ ICE
Output	ICE	21.236	0.000	ICE → Output
ICE	Output	0.691	0.708	Output $\nrightarrow$ ICE
Hours worked	ICE	15.057	0.001	ICE → Hours worked
ICE	Hours worked	3.482	0.175	Hours worked $\nrightarrow$ ICE

Note: We perform two-variables (i.e ICE with household investment, residential investment, durable goods, business investment, output and hours worked) VAR model for Granger-causality test. AIC is used for lag selection for each VAR regression. We take natural log for household investment, residential investment, durable goods, business investment, output and hours worked. A variable that Granger-causes another variable at 5% significance level is in bold.

Table 2.2: Cross-correlations conditional on ICE shock

	$j = -4$	-3	-2	-1	0	1	2	3	4
$Corr(HI_t, Y_{t+j} ICE^{shock})$	0.468	0.544	0.624	0.702	0.772	0.806	0.811	0.797	0.771
$Corr(HI_t, HW_{t+j} ICE^{shock})$	0.224	0.263	0.309	0.360	0.408	0.439	0.448	0.440	0.417

Note: The table presents cross correlation between household investment in t with output and total hours worked in $t + j$ on conditional consumer confidence shocks in VAR system for the period 1961Q1 to 2017Q4. The largest correlations are shown in bold.

Table 2.3: Results: ICE residuals on TFP growth and RPI growth

	(1)	(2)
Variables	One-step ahead	Four-step ahead
TFP growth	-0.361 (0.639)	-0.230 (0.636)
RPI growth	1.057 (0.885)	-0.601 (-0.601)
Constant	0.007 (0.007)	-0.003 (0.007)
Observations	228	228
R-squared	0.008	0.003

Note: Standard errors in parentheses. We regress ICE residuals (the residuals from four variables, ICE, household investment, hours worked and output in VAR system) on first lag of TFP growth and RPI growth in Column (1) and on fourth lag of TFP growth and RPI growth in Column (2). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2.1: Consumer confidence and household investment

Note: The NBER recession dates are in grey shading. The series of data are in level. The ICE and household investment are in right and left scales, respectively. The sample period is 1960Q1 to 2017Q4.

Figure 2.2: Main data used for analysis

Note: We plot US quarterly real residential investment, real expenditure on durable goods, housing starts, real output, business investment and hours worked in panels (a)–(f) respectively. The sample period is 1960Q1 to 2017Q4.

Figure 2.3: Cross-correlations: ICE (t) with a variable ($t + j$)

(a) ICE (t) and Household investment ($t+j$)

(b) ICE (t) and Housing starts ($t+j$)

(c) ICE (t) and Output ($t+j$)

(d) ICE (t) and Business confidence ($t+j$)

(e) ICE (t) and Hours worked ($t+j$)

(f) ICE (t) and Business investment ($t+j$)

Note: All series (except ICE and business confidence index) are logged and de-trended with the HP-filter ($\lambda = 1600$). The sample period is 1960Q1 to 2017Q4.

Figure 2.4: Responses to a one standard deviation consumer confidence shock (ICE ordered first)

Note: These are IRFs from a four-variables VAR with ICE, household investment, hours worked and output based on Cholesky identification. ICE is ordered first in the VAR. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.5: Responses to a one standard deviation consumer confidence shock (ICE ordered last)

Note: These are IRFs from a four-variables VAR with ICE, household investment, hours worked and output. ICE is ordered at last in the VAR. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.6: Decomposition of variance of ICE innovations

Note: This figure plots variance decompositions from the four-variable VAR whose impulse responses are shown in [Figure 2.4](#) and [Figure 2.5](#) under both orderings. The sample period is 1960Q1 to 2017Q4.

Figure 2.7: Responses to consumer confidence shock: the role of household investment in the transmission channel

Note: These are IRFs from a four-variables VAR with ICE, household investment, hours worked and output. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.8: Responses to a one standard deviation consumer confidence shock

Note: These are IRFs from a four-variables VAR with ICE, household investment, hours worked and business Investment. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.9: Responses to a one standard deviation consumer confidence shock: Larger
VAR

Note: These are IRFs from a six-variables VAR with ICE, household investment, business investment, government expenditure, hours worked and output. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.10: Historical forecast error decomposition of ICE shocks

(a) ICE to ICE

(b) Household investment to ICE

(c) Hours worked to ICE

(d) Output to ICE

Note: These are historical decomposition from a four-variables VAR with ICE, household investment, hours worked and output. The sample period is 1960Q1 to 2017Q4.

Figure 2.11: Robustness: Responses to a one standard deviation confidence shock
(1960Q1 to 2017Q4)

Note: These are IRFs from a five-variables VAR with ordering ICE, nominal interest rate, household investment, hours worked and output. We take natural log for all variables except for nominal interest rate. The shaded areas are one-standard-error confidence bands from [Kilian \(1998\)](#) bias-corrected bootstrap after bootstrap. The sample period is 1960Q1 to 2017Q4.

Figure 3.13: Decomposition of the variance of the five variables due to ICE innovations

Note: This figure plots variance decompositions from ICE innovations in the five-variables VAR system with ordering ICE, nominal interest rate, household investment, hours worked and output. We take natural log for all variables except for nominal interest rate. The sample period is 1960Q1 to 2017Q4.

Note: These are IRFs from an eight-variables VAR with ordering stock return, ICE, nominal interest rate, TFP, RPI, household investment, hours worked and output based on Cholesky identification. BCI is ordered first in the VAR. We take natural log for all variables except for nominal interest rate. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Note: This figure plots variance decompositions from the eight-variables VAR with ordering stock return, ICE, nominal interest rate, TFP, RPI, household investment, hours worked and output, and their impulse responses are shown in [Figure 2.13](#). We take natural log for all variables except for nominal interest rate. The sample period is 1960Q1 to 2017Q4.

Note: These are IRFs from an eight-variables VAR with ordering term spread, ICE, nominal interest rate, TFP, RPI, household investment, hours worked and output based on Cholesky identification. BCI is ordered first in the VAR. We take natural log for all variables except for nominal interest rate. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.16: Robustness: Responses to a one standard deviation confidence shock (ICE ordered first)

Note: These are IRFs from a four-variables VAR with ICE, household investment, hours worked and output. ICE is ordered at first. The shaded areas are one-standard-error confidence bands from [Kilian \(1998\)](#) bias-corrected bootstrap after bootstrap. The sample period is 1985Q1 to 2017Q4.

Figure 2.17: Robustness: Responses to a one standard deviation confidence shock (ICE ordered last)

Note: These are IRFs from a four-variables VAR with ICE, household investment, hours worked and output. ICE is ordered at last. The shaded areas are one-standard-error confidence bands from [Kilian \(1998\)](#) bias-corrected bootstrap after bootstrap. The sample period is 1985Q1 to 2017Q4.

Figure 2.18: Decomposition of the variance of the impulse responses of ICE due to ICE innovations

Note: This figure plots variance decompositions from the four-variable VAR whose impulse responses are shown in [Figure 2.16](#) and [Figure 2.17](#) under both orderings. The sample period is 1985Q1 to 2017Q4.

Figure 2 19: Responses to a one standard deviation consumer confidence shock

Note: These are IRFs from a four-variables VAR with ICE (ordered first), household investment, unemployment rate and output. We take natural log for all variables except for unemployment rate. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.20: Responses to a one standard deviation consumer confidence shock, holding fixed hours worked responses to ICE shocks at all forecast horizons

Note: These are IRFs from a four-variables VAR with ICE (ordered first), household investment, hours worked and output. We shut down the direct responses of hours worked to confidence shocks at all forecast horizons. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in Kilian (1998). The sample period is 1960Q1 to 2017Q4.

Figure 2.21: Responses to a one standard deviation consumer confidence shock: residential investment case

Note: These are IRFs from a four-variables VAR with ICE, residential investment, hours worked and output. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure 2.22: Responses to a one standard deviation consumer confidence shock: the durable goods case

Note: These are IRFs from a four-variables VAR with ICE, durable goods, hours worked and output. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Note: These are IRFs from a five-variables SVAR with ICE, durable goods, durable goods industrial production, hours worked and output. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1985Q1 to 2017Q4.

Chapter 3

Uncertainty and Inventory

Investment

3.1 Introduction

Both uncertainty and inventory investment have long been viewed as important for studying business cycle fluctuations. For example, [Blinder and Maccini \(1991\)](#) document that declines in inventory investment account for as much as 87% of the total peak-to-trough movement in Gross National Product (GNP) during the average postwar US recessions.¹ Theoretical and empirical investigations identify that uncertainty is a potential factor in shaping aggregate economic outcomes (see, for example, [Caballero and Pindyck \(1996\)](#); [Bloom \(2009\)](#); [Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry \(2018\)](#)) and it affects firm's capital expenditure through several

¹[Maccini, Moore and Schaller \(2015\)](#) show that in the 2007–09 recession, inventories accounted for one-third of the fall in US GDP, a huge amount for such a small component of output.

channels (see, for example, [Bernanke \(1983\)](#); [Leahy and Whited \(1996\)](#); [Hennessy and Whited \(2007\)](#)). Somewhat surprisingly, however, little is known on the direct effect of uncertainty on firms' inventory investment. My paper fills this gap.

I explore the effect of uncertainty on firms' inventory behaviour. More specifically, I empirically investigate the effect of idiosyncratic profit uncertainty for US manufacturing firms' inventory investment, using an unbalanced panel data from Compustat for the period 1981–2017. I follow the literature and consider the stock adjustment model of [Lovell \(1961\)](#). I implement a dynamic error-correction inventory model, controlling for financial variables such as liquidity and coverage ratio.

I use the profit function approach to construct the profit idiosyncratic uncertainty. [Ghosal and Loungani \(2000\)](#) construct an annual measure of profit uncertainty based on industry profit to investigate the capital investment.² They use 3-year (or more) moving average standard deviation of the residuals from profit function estimation to measure profit uncertainty. This uncertainty may have serial correlation problems because of the moving average. In the recent literature, [Byun and Jo \(2018\)](#) use aggregate profit uncertainty as the conditional standard deviation of a common factor across unforecasted fluctuations of the industry's sales revenue to examine the firm-level capital investment, using quarterly data. However, the uncertainty measure in my paper is different than theirs because I construct yearly firm-level idiosyncratic uncertainty using standard deviation within a year from a large quarterly data.³ To the best knowledge, this is the first attempt at constructing firm-level profit uncer-

²[Caglayan, Maioli and Mateut \(2012\)](#) use sales uncertainty to investigate firm's inventory behaviour in European countries.

³[Bloom, Bond and Van Reenen \(2007\)](#) use standard deviation of firms' monthly return to construct uncertainty within-year to examine the capital investment.

tainty using a large quarterly data set and examining its role on US firms' inventory behavior.

Previous literature studied firms' inventory behavior in the presence of asymmetric information. [Kashyap, Lamont and Stein \(1994\)](#) show that cost of finance affects inventory investment. They provide evidence that the bank dependent and liquidity constrained firms—without access to public debt markets—reduce their inventories significantly in the 1981–1982 US recession. [Carpenter, Fazzari and Petersen \(1994\)](#), [Guariglia \(1999\)](#), [Benito \(2005\)](#), [Guariglia and Mateut \(2006\)](#) argue that financial friction markets can constrain inventory investment decisions and force firms to rely on internal funds.

Although the role of uncertainty in determining firm's capital investment has been extensively studied in the literature, its role for inventory investment has not received much attention.⁴ [Lee and Koray \(1994\)](#) examine the relationship between sales uncertainty and inventory behavior for the US wholesale and retail trade sector and show that the variance in sales does not affect inventory behavior in either sector. However, they use multivariate time-series model with time-varying conditional variances to examine those issues. [Caglayan, Maioli and Mateut \(2012\)](#) investigate the impact of sales uncertainty on firm's inventory behavior in six European countries (i.e Belgium, Finland, France, Italy, Portugal, and Spain) and find that sales uncertainty has positive effect on inventory investment. Firms might face adverse selection and moral hazard problems in the capital market since the supply of external funds is

⁴See, for example, [Bloom, Bond and Van Reenen \(2007\)](#); [Gilchrist, Sim and Zakrajsek \(2014\)](#). They show that the fluctuations in uncertainty have large effects on capital investment.

not perfectly elastic. The role of profit uncertainty in determining firms' inventory behavior in the presence of asymmetric information is, however, little known in the literature.

I find that the effect of profit uncertainty on firms' inventory investment is positive and statistically significant. It suggests that US manufacturing firms increase their inventory stocks significantly for precautionary motive to avoid running out of stocks under higher profit uncertainty. The result supports the stock-out avoidance model in [Kahn \(1987, 1992\)](#), where they provide evidence that the stockout-avoidance motive is a reason for holding inventories. I also find that uncertainty has a direct effect on firms' inventory investment and not through the balance sheet or liquidity channel as emphasized in the transmission of monetary policy. These findings motivate me to investigate further whether the firms' characteristics are important for inventory investment when firms are uncertain about the future profits.

I also study the effect of uncertainty for each component of inventory investment, which includes raw materials, work-in-progress and finished goods for the period 2004–2017.⁵ I show that each component of the inventory investments is positively related with higher uncertainty. To my best knowledge, this is a new finding in the literature.

Having established the positive relationship between profit uncertainty and inventory investment, I explore whether or not this relationship is different in firms' characteristics such as small versus large, bank-dependent vs bond-rated and high

⁵The components of inventory series are only available in Compustat with sufficient coverage from the year 2004.

leverage versus low leverage.⁶ The firms' characteristics are important for inventory behavior in higher uncertainty since some firms might not access low cost finance because of their balance sheet position and the asymmetric informations. First, I find that large firms increase inventory stocks with higher idiosyncratic profit uncertainty. However, small firms do not appear to increase the stocks when uncertainty is higher. Second, I find that the effect of uncertainty is positive on inventory investment for both bank-dependent and bond-rated firms. However, the effect of uncertainty on inventory investment is lower for bank-dependent firms than for bond-rated firms. This result suggests that the bank lending channel has little impact on firms' inventory investment with higher uncertainty.

Third, I find that high leverage firms accumulate the inventories under profit uncertainty. This suggests that they invest for inventory stocks to avoid the stock-out problems even though they face tightened financial constraints. Firms with high leverage or high levels of debt relative to assets might be forward looking and risk taker firms. Firms' forward-looking investment decisions force them to increase inventory stocks under higher uncertainty for risky ventures. However, low leverage firms do not appear to increase the inventories with higher uncertainty.

The rest of the paper is organized as follows. In section 3.2, I include the related literature. In section 3.3, I provide the empirical model for inventory investment growth, data sources and variables construction, measure of idiosyncratic profit uncertainty and descriptive analysis. In section 3.4, I analyze the empirical results from

⁶Researchers have extensively used these characteristics to identify the financial constraints. See, for example, Kashyap, Lamont and Stein (1994), Carpenter, Fazzari and Petersen (1994, 1998) and Dasgupta, Li and Yan (2019)

the inventory investment growth model. In section 3.5, I present robustness checks, and section 3.6 concludes.

3.2 Related literature

The paper is related to a growing literature studying the role of uncertainty and capital market imperfection on macroeconomics dynamics. In the literature, theoretical and empirical investigations identify that several channels through which uncertainty affect firm's capital investment. For example, [Bernanke \(1983\)](#) analyzes the irreversible choice of capital, which causes firms to wait for information under high uncertainty; [Dixit and Pindyck \(1994\)](#) highlight the effect of irreversibility of the capital due to sunk costs with uncertain consequences; [Leahy and Whited \(1996\)](#) find that uncertainty exerts a strong direct negative effect on capital expenditure; [Bloom, Bond and Van Reenen \(2007\)](#) show higher uncertainty with partial irreversibility reduces the impact effect of demand shocks on investment and increases real option values making firms more cautious when investing or disinvesting. In recent literature, [Barro, Bloom and Wright \(2017\)](#) show that highly-levered firms exhibit larger declines in capital expenditure, R&D, and hiring in times of higher short- and long-run uncertainty. The existing literature is, however, little known about the direct effects of uncertainty on firms' inventory investment.

The capital market imperfections literature shows that corporate investment is sensitive to internal funds if financial constraints are effective. [Gertler and Gilchrist \(1994\)](#) find that small firms significantly reduce their real activities relative to large

firms following tightened monetary policy. [Carpenter, Fazzari and Petersen \(1994, 1998\)](#) find that small firms are more dependent on cash flows to finance investment and argue that firm size is a proxy for ability to access external capital markets. [Dasgupta, Li and Yan \(2019\)](#) build a model that studies the interaction of the financial constraints and inventory behaviour. They show that the financial constrained firms are unable to build inventory when costs are low and deplete inventory when costs are high. However, these papers do not consider the effect of profit uncertainty on firm's inventory investment in asymmetric information as I consider in this paper.

[Jones and Tuzel \(2013\)](#) build a model, using a factor of production together with capital, and examine the effects of cost of capital on inventory investment. They use time series and cross section data and provide evidence that risk premium rather than real interest rate, is negatively related to future inventory growth. They also find a stronger relationship between risk premium and inventory growth for durable goods than for non-durable goods. [Belo and Lin \(2012\)](#) also use a a factor of production model with convex and non-convex adjustment costs to examine the relation between stock returns and inventory growth rate. They provide evidence that firms with lower inventory growth rate outperform firms with higher inventory growth rate. My focus in this paper is to empirically investigate the relationship between profit uncertainty and inventory growth in contrast to the risk premium from the capital market.

3.3 Econometric model

In this section, I discuss about the empirical inventory investment model, measure of profit idiosyncratic uncertainty, data sources and construction of variables. I also include descriptive statistics of the variables.

3.3.1 Inventory investment model

In early strand of literature, [Metzler \(1941\)](#) documents that an inventory accelerator is a powerful de-stabilizer that can produce cycles in a simple Keynesian model. Following him, many researchers use inventory behavior models based on microeconomics principles such as production smoothing model (see, for example, [Darling and Lovell \(1971\)](#)), stock-out avoidance model (see, for example, [Kahn \(1987\)](#)), stock adjustment model (see, for example, [Lovell \(1961\)](#)), (S,s) inventory model (see, for example, [Blinder, Lovell and Summers \(1981\)](#)), to explain firms' inventory holding behavior.

I follow a stock adjustment model from [Lovell \(1961\)](#) to investigate the effect of profit uncertainty on inventory investment, empirically.⁷ The baseline specification is:⁸

$$\Delta I_{it} = \beta_1 \Delta I_{it-1} + \beta_2 \Delta S_{it} + \beta_3 \Delta S_{it-1} + \alpha(I_{it-1} - S_{it-1}) + \phi LIQ_{it} + \gamma \sigma_{it} + \nu_i + v_t + \kappa_{it} \quad (3.3.1)$$

⁷I provide theoretical motivation for inventory investment model in Appendix.

⁸[Guariglia and Mateut \(2010\)](#), [Caglayan, Maioli and Mateut \(2012\)](#), [Jones and Tuzel \(2013\)](#) and among others use similar baseline specification to estimate inventory investment growth.

where, ΔI_{it} is inventory investment growth and ΔI_{it-1} is a dynamic term, lagged value of inventory growth. I expect negative sign from the dynamic term. I use ΔS_{it} and ΔS_{it-1} to denote current sales growth and one-lagged value of sales growth, respectively. The expected sign for current and previous sales growth are positive. I include an error correction term $(I_{it-1} - S_{it-1})$, which arises from the motive of target adjustment in [Lovell \(1961\)](#) and captures the long-run target inventory level. I expect a coefficient associated with the error correction term should be negative. I choose liquidity, LIQ_{it} , to control for financial variables. [Kashyap, Lamont and Stein \(1994\)](#) argue that liquidity is the most important determinant of inventory investment growth. I use σ_{it} to denote idiosyncratic profit uncertainty and expect a positive sign from the coefficient of uncertainty for inventory investment growth. Let ν_i , be a firm-specific component; v_t be a time-specific component accounting for possible macroeconomic effects, and more specifically for effects due to changes in monetary policy; and κ_{it} be an idiosyncratic component of error term. The details of variable definition are in [Table 3.1](#).

3.3.2 Measure of profit uncertainty

I define profit uncertainty based on firm's sales revenue.⁹ I choose sales revenue with two reasons. First, it is a fundamental source of firm's periodic profits from operating activities. Second, the gross profit is occasionally negative and differs from sales only up to a constant under the assumption of a Cobb-Douglas production function.

⁹[Herskovic, Kelly, Lustig and Nieuwerburgh \(2016\)](#) find a strong factor structure in idiosyncratic volatilities in firm's sales growth. They show that the common factor in sales growth volatility follows the same low frequency patterns as the common factor in idiosyncratic return volatilities.

I use the profit function to calculate idiosyncratic profit uncertainty, following [Gilchrist, Sim and Zakrajsek \(2014\)](#) approach:¹⁰

$$\Delta \log S_{it_q} = c_{it_q} + \alpha \Delta \log K_{i,t_q-1} + \lambda_{jt_q} + u_{it_q}, \quad (3.3.2)$$

where i indexes firm and t_q , $q = 1, 2, 3$ and 4 , quarters in year t , S_{it_q} is quarterly sales revenue, and K_{it_q} is the quarterly capital stock of firm i . I use λ_{jt_q} to denote industry-specific (2-digit SIC code) time fixed effects to control for the persistent nature of cyclical profitability shocks within an industry. I also include c_{it_q} , firm specific quarterly dummies, to control for a seasonal pattern:

$$c_{it_q} = \sum_{n=1}^4 \phi_n \times \mathbf{1}[QTR_{it_q} = n], \quad (3.3.3)$$

where $\mathbf{1}[QTR_{it_q} = n]$ is an indicator function that equals one if firm i observation in period t_q falls in quarter n and zero otherwise.

I use $\hat{u}_{it_q}$, the residuals, from the estimation of equation (3.3.2) to get the process for idiosyncratic profit shock. I then use pooled Ordinary Least Square (OLS) regression to obtain the persistence of the process as follows:

$$\hat{u}_{it_q} = \beta \hat{u}_{i,t_q-1} + e_{it_q}. \quad (3.3.4)$$

Following the similar approach of [McConnell and Perez-Quiros \(2000\)](#), I get unbi-

¹⁰They use this approach to investigate the macroeconomics implications with idiosyncratic uncertainty based on profits.

ased estimator of the true value of e_{it_q} and I assume that error term e_{it_q} in regression equation (3.3.4) is normally distributed.¹¹ The unbiased estimator is given by:

$$\hat{\epsilon}_{it_q} = \sqrt{\frac{\pi}{2} |\hat{e}_{it_q}|}, \quad (3.3.5)$$

which yields an estimate of the volatility of idiosyncratic profit shocks for each firm i in every quarter, t_q .

In the next step, I calculate the yearly firm-specific standard deviation of quarterly idiosyncratic operating returns as follows:

$$\hat{\sigma}_{it} = \sqrt{\left[\frac{1}{4} \sum_{q=1}^4 (\hat{\epsilon}_{it_q} - \bar{\epsilon}_{it})^2 \right]}, \quad (3.3.6)$$

where $\hat{\epsilon}_{it_q}$ denotes the OLS residual—the idiosyncratic returns—from equations (3.3.4) and (3.3.5), and $\bar{\epsilon}_{it}$ is the sample mean of quarterly idiosyncratic returns in year t .

$$\bar{\epsilon}_{it} = \frac{1}{4} \sum_{q=1}^4 \hat{\epsilon}_{it_q}. \quad (3.3.7)$$

We use $\hat{\sigma}_{it}$ from equation (3.3.6) as measure of time-varying profit uncertainty for firm i for inventory investment estimation.

¹¹They use this approach to estimate the GDP growth as an AR(1) to test structural break in the residual variance.

3.3.3 Data

I use Compustat quarterly and annual data sample for the period 1981–2017. First, I use quarterly database of all US non-financial firms to calculate the idiosyncratic profit uncertainty. So, I exclude financial, insurance, and real estate firms (SIC code 6000-6900), and utilities (SIC code 4900-4999) for quarterly data. I also exclude any firm-quarter observation that has missing sales revenue (sales turnover, Compustat # SALE) and capital stock (net property, plant, and equipment, Compustat # PPENT) from the sample. To ensure that the results are not driven by a small number of extreme observations, I drop from the sample all observations with the sales-to-capital ratio below 0.01 and above 20. I also restrict the sample to firms with at least 16 quarters of data. The final quarterly dataset is an unbalanced panel of 12,910 firms for a total of 657,852 observations.

Second, I use the annual Compustat database of US manufacturing firms (SIC code 2000–3999) to evaluate the effects of profit uncertainty on firms’ inventory behavior. I drop from the sample observations if firms have total assets less than \$10 million, following [Carpenter, Fazzari and Petersen \(1994\)](#). These firms are frequently start-up companies with zero sales and negative cash flow. I drop from the sample that has missing uncertainty, inventory investment, sales and liquidity. In addition, to alleviate the impact of outliers, I winsorize inventory and sales scaled by lagged capital 1% level at both tails of the distribution. The final dataset is an unbalanced panel consisting of 60,857 firm-year observations. I use GDP implicit price deflator to convert real values from all nominal values. [Table 3.1](#) provides the definition of variables.

Table 3.1: Definition of variables

Variables	Definition
σ_{it}	Idiosyncratic profit uncertainty based on the profit function (see section 3.3.2)
ΔI_{it}	Log difference of inventory investment (#INVT)
ΔS_{it}	Log difference of sales revenue (#SALE)
TA_{it}	Total assets (#AT)
K_{it}	Capital stock defined as net property, plant and equipment (#PPENT)
$I_{it} - S_{it}$	Log difference of inventory investment (#INVT) and sales revenue (#SALE)
LIQ_{it}	Cash and short-term investments (#CHE) scaled by beginning period of the total assets (#AT)
CF_{it}	Cash flow scaled by beginning period of total assets, income before extraordinary items (#IBC) plus depreciation and amortization (#DPC)
Lev_{it}	Ratio between the sum of short-term debt in current (#DLC) and long-term debt liabilities (#DLTT), and the beginning year value of total assets (#AT)
COV_{it}	Ratio between interest expenses (#XINT) and sum of interest expenses and cash flows (#IBC+#DPC)

Note: I use Compustat quarterly and annual data sample for the period 1981–2017. I exclude financial, insurance, and real estate firms (SIC code 6000–6900), and utilities (SIC code 4900–4999) for quarterly data to obtain the uncertainty. I use manufacturing firms (SIC code 2000–3999) to evaluate the effects of profit uncertainty for firm’s inventory behaviour.

3.3.4 Descriptive statistics

Table 3.2 shows the descriptive statistics of main variables used in the analysis for full sample. The total observations are 60,857 and number of firms are 4,379. The mean value of inventories growth, sales growth, liquidity and uncertainty is positive over the sample period. The mean value of difference between inventory and sales is negative. The uncertainty has the lowest standard deviation, and difference between inventory and sales has the highest one. The median and mean value of inventory growth, sales growth, and difference between inventory and sales are almost same.

Table 3.3 reports the descriptive statistics of the variables for split sample, according to the firm size and bond-ratings groups. Panel (A) refers to the small firm and large firms based on the firm size. The total observations for small and large firms are 30,428 and 30,429. The average values of inventory growth and sales growth for small firms are lower than for large firms. But, average value of liquidity for small firms is higher than for large firms. The standard deviation of each variable for small firms is higher than for large firms. It implies that small firms are more volatile than large firms.

Panel (B) refers to the bank-dependent and bond-rated firms based on bond rating. The total observations for bank-dependent and bond-rated firms are 22,275 and 38,582, respectively. The average values of inventory growth, sales growth and liquidity for bank-dependent firms are lower than for bond-rated firms. The standard deviation of uncertainty, inventory growth and sales growth for bank-dependent firms are higher than for bond-rated firms. However, the standard deviations of difference between inventory investment and sales, and liquidity for bank-dependent firms are low compared to bond-rated firms.

3.4 Empirical analysis

In this section, I provide the estimation procedure of inventory investment model and discuss the baseline results. I also consider the components of the inventory investment and provide the results for each of them. Finally, I examine the effects of uncertainty on inventory investment based different characteristics of firms such as

firms size.

3.4.1 GMM estimation

I employ the [Arellano and Bond \(1991\)](#) first-difference Generalized Method of Moments (GMM) approach to estimate the inventory investment equation.¹² This approach eliminates the unobserved firm-specific effects from the first-differenced equations by the transformation. All lagged variables are valid instruments in first-differencing for the transformed equation conditional on the error terms.

I perform [Arellano and Bond \(1991\)](#) Autocorrelation (AR) test for first-, second- and third-order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation. Since the instrument variable sets should be uncorrelated with the error term in the relevant equation, I use the Hansen J test of the overidentifying restrictions, under the null of instrument validity, is asymptotically distributed as a chi-square with degrees of freedom equal to the number of instruments less the number of parameters. I estimate the two-step GMM method with robust standard errors.¹³ In the first step, homoskedasticity and independent error terms are assumed. In the second step, these assumptions are relaxed by using a consistent variance-covariance matrix that is constructed from the first step residuals.

¹²Applying OLS to this empirical problem, in general, is that lagged dependent variable is correlated with the fixed effects in the error term, which gives rise to “dynamic panel bias” [Nickell \(1981\)](#).

¹³I implement the command `xtabond2` from [Roodman \(2009\)](#) in Stata for estimation.

3.4.2 Baseline results

I estimate equation (3.3.1) using first-difference GMM approach to examine the role of uncertainty for inventory investment growth. I treat the lagged dependent variables as endogenous variables and other regressors as exogenous. I assume that uncertainty—a generated variable—is exogenous for two reasons. First, I generate an uncertainty variable within a panel of 12,910 non-financial firms (total observations 657,852) and use this variable as a regressor to estimate inventory investment for 4,379 manufacturing firms (total observations 60,857). Second is that this uncertainty variable is a second moment of unobserved part of the non-financial firms within a year, using quarterly dataset.

I perform an AR test and the Hansen J over-identifying restrictions test to check the model choice and report the p -value for these tests for all specifications. The hypothesis that there is no significant evidence of first- and second-order serial correlation in the first-differenced residuals is rejected at 5% level. So, I use three and further lags of each of the endogenous variables as instruments.¹⁴ The hypothesis that there is no significant evidence of third-order serial correlation in the first-differenced residuals is not rejected at the 5% level for most of the estimations.¹⁵ The later test rejects the null hypothesis that the instrument variables are correlated with the error term and the equation is misspecified. I also report the robust standard errors with the coefficient in parentheses.

¹⁴See [Brown and Petersen \(2009\)](#) use three to six lags of variables as instruments

¹⁵I use second and further lags (or fourth and further lags) of dependent variable as instruments. The result are qualitatively same.

Table 3.4 shows the results. Column (1) shows the baseline results without uncertainty variable. The coefficient of a dynamic term—lagged value of dependent variable—is -0.270 and statistically significant. It explains that one percent increase in past inventory position of manufacturing firms decreases the current inventory adjustment on average by 0.27 percent. The coefficient of current sales growth is 0.786, which implies that current sales growth has positive relationship with current inventory growth and it is statistically significant. The coefficient of past sales growth also is 0.0534, which is lower than of current sales growth and statistically significant at 10% level. I observe that the coefficient of an error correction term—which is the difference between inventory and sales—is -0.875 and statistically significant. It explains that the increase in the difference between inventory and sales has negative long-run relationship with inventories. This finding implies that if the inventory stocks are higher than the desired level of stocks, the future inventory investment accumulation should be lower and vice-versa. Liquidity has negative effect for inventory growth since its coefficient is -0.141 and statistically significant, and implies that increasing the cash stocks will reduce the stocks of inventories in the US manufacturing firms.

Column (2) displays the results with the uncertainty variable in the baseline equation. The coefficient of the uncertainty variable is 0.117 and statistically significant. One-unit increase in uncertainty will decrease inventory growth on average by 0.117 percentage points. US manufacturing firms' inventory investments appear to be positively driving with higher profit uncertainty. This result suggests that firms accumulate inventories with higher uncertainty for precautionary motive to avoid risks of stocks-out. Kahn (1987) argue that actually firms hold inventories not for production

smooth but for costly stocks-out. [Kahn \(1992\)](#) provide evidence that the stocks-out avoidance motive is a reason for holding inventories, using the US automobile industry data. In column (3) to (6) display the result for the different specifications.

Motivated by [Carpenter, Fazzari and Petersen \(1994, 1998\)](#) and [Benito \(2005\)](#), I also consider cash flows and coverage ratio variables as control variables in the model. I next estimate the model with cash flows variable instead of liquidity variable and present the results in Column (3). I observe that cash flow variable is negative and statistically insignificant but the uncertainty variable is positive and statistically significant as before. [Guariglia and Mateut \(2010\)](#) and [Caglayan, Maioli and Mateut \(2012\)](#) also find that cash flow is a poor determinant for inventory growth model.¹⁶ I also estimate the model, controlling for cash flow and coverage ratio in Column (4). However, these variables, cash flow and coverage ratio are statistically insignificant. So I consistently use liquidity variable instead of cash flow as a financial control variable for all the specifications.

I next evaluate the implications of profit uncertainty on inventory growth, considering an interaction term of uncertainty and liquidity in the baseline model since this interaction term may reflect how the liquidity channel is important. Column (5) shows the results. The coefficient of liquidity and uncertainty are negative and positive as before, respectively, and statistically significant. However, the coefficient of the interaction term is statistically insignificant at 10% level. This implies that uncertainty does not impact to inventory growth through the liquidity constraints

¹⁶[Guariglia and Mateut \(2010\)](#) study the role of MIX (the ratio of the short-term debt to the sum of its short-term debt and trade credit) variable for inventory investment using UK manufacturing firms and [Caglayan, Maioli and Mateut \(2012\)](#) study the role of uncertainty for inventory investment using European countries firms data.

channel.¹⁷ Perhaps, the firms' characteristics such as firm size and leverage, are important for inventory behavior in the higher uncertainty since some firms might not access low cost finance because of their balance sheet position.

Alternatively, one might argue that the uncertainty affects the inventory growth through balance sheet channel in the transmission of monetary policy.¹⁸ To deal with this issue, I also include coverage ratio, and interaction term of coverage ratio and uncertainty in the model and show the results in Column (6). Both variables, coverage ratio and interaction term of coverage and uncertainty are statistically insignificant. This result implies that the effect of uncertainty in determining firm's inventory investment is direct not through the balance sheet or liquidity channel.

Overall, this findings suggest that US manufacturing firms increase their inventory stocks significantly for precautionary motive to avoid running out of stocks under higher profit uncertainty. Balance sheet or liquidity channel is not important for firm's inventory investment decision. This findings motivate me to investigate further whether the firms' characteristics such as firm size and leverage, are important for inventory growth when firms are uncertain about the future profit.

3.4.3 Components of inventory investment

I study the effect of uncertainty for each component of firms' inventory investment, which includes raw materials, work-in-progress and finished goods.¹⁹ The components

¹⁷For some European countries, for example, Finland, Italy, Portugal and Spain, [Caglayan, Maioli and Mateut \(2012\)](#) provide evidence that liquidity is not uncertainty channel to affect the inventory investment, using firm level data.

¹⁸[Bernanke and Gertler \(1995\)](#) argue that coverage ratio is an important measure of firm's balance sheet.

¹⁹I exclude other inventory component since the data are not sufficiently available in Compustat.

of inventory series are only available in Compustat with sufficient coverage from the year 2004. I then estimate the baseline inventory investment model to investigate the effects of uncertainty on each component. [Table 3.5](#) shows the results. Column (1) display the results for aggregate inventory investment for the period 2004–2017. The coefficient of uncertainty is 0.183, which is bigger than the coefficient of uncertainty for full sample in [Table 3.4](#). It is statistically significant. Column (2), (4) and (6) show the results from baseline model for raw materials, work-in-progress and finished goods, respectively. The coefficients of uncertainty are 0.238, 0.205 and 0.192 for raw materials, work-in-progress and finished goods, respectively. These coefficients are statistically significant. This results imply that one-unit increase in uncertainty will increase firms’ raw materials, work-in-progress and finished goods on average by 0.238, 0.205 and 0.192 percentage points, respectively.

Column (3), (5) and (7) display the results, adding the interaction term of uncertainty and liquidity in the baseline model. The interaction term is positive, but statistically insignificant for all components of inventory investments. However, the coefficient of the uncertainty is bigger than from the baseline model and statistically significant. For all these estimation, the hypothesis that there is no significant evidence of third-order serial correlation in the first-differenced residuals is not rejected and Hansen J test does not reject the validity of the over-identifying restrictions. The results of the each component is qualitatively similar to the aggregate inventory investment. The findings suggest that each component (i.e. raw materials, work-in-progress and finished goods) of the inventory investment of US manufacturing firms is positively related with profit uncertainty. This is a new finding in the literature.

3.4.4 Firm Characteristics and Uncertainty

Having established positive relationship between idiosyncratic uncertainty and US manufacturing firm's inventory behavior, I explore how this relationship differs with different characteristics firms. There are different measures to separate firms into groups to a priori criteria that identify the firms' characteristics. I divide firms according to firm size, bond ratings and leverage ratio.

Firm size

I split the sample by firm size, which is one of the most commonly used in the literature (see, for example, [Gertler and Gilchrist \(1994\)](#); [Carpenter, Fazzari and Petersen \(1998\)](#)). I define a small firm if a firm is below the median of the total assets in total observations and, a large firm otherwise.²⁰ Splitting the sample allows both groups to have different intercepts and different sensitivities to the financial and non-financial variables.

I estimate the equation (3.3.1) to examine the inventory investment sensitivity to uncertainty for small and large firms. [Table 3.6](#) shows the results. Column (1) and (3) present the results from baseline model for small and large firms, respectively. The coefficient of uncertainty for small firms is positive but statistically insignificant at 10% level. This is positive and statistically significant for large firms, and also bigger than for small firms. The finding suggests that small firms do not increase inventory stocks under higher uncertainty. However, the higher uncertainty drives large firms'

²⁰In recent literature, [Dasgupta, Li and Yan \(2019\)](#) define an unconstrained firm according to the top 30% of beginning period of the book value of assets and a constrained firm to the bottom 30%.

inventory stocks positively.

Adding interaction term of uncertainty and liquidity, I examine whether the effect of uncertainty on firms' inventory investment via cash stocks. Column (2) and (4) show the results for small and large firms, respectively. For small firms, uncertainty and interaction term are statistically insignificant but these variables are statistically significant for large firms.

Bond ratings

Next, I use another commonly used firm's classifications, which is based bond ratings (see, for example, [Kashyap, Lamont and Stein \(1994\)](#)), to assess firms' inventory investment under higher profit uncertainty. I define a bank-dependent firm if a firm that does not have a bond rating from Standard and Poors at the beginning of the year and, a bond-rated firm otherwise. I show the results in [Table 3.7](#). Column (1) and (3) show the results from baseline model for bank dependent firms and bond-rated firms, respectively. For both types of firms, the coefficient of uncertainty is positive and statistically significant at 5% level but it is little bit small for bank-dependent firms compared to bond-rated firms. Column (2) and (4) display the results for bank-dependent and bond-rated firms, respectively, when I estimate the model with interaction term of liquidity and uncertainty. I find that uncertainty affects inventory investment directly for both types of firms. This result suggests that the lending channel has little effect for inventory investment since the bank dependent firms also increase inventory stocks when profit uncertainty exists.

Leverage

I then explore how this positive relationship between idiosyncratic profit uncertainty and inventory investment differs for firms based on leverage. I calculate the leverage measure for each firm-year in following way—the ratio between the sum of short-term debt and long-term debt liabilities, and the beginning year value of total assets:

$$LEV_{it} = \frac{DebtShortTerm_{it} + DebtLongTerm_{it}}{TA_{it-1}}. \quad (3.4.1)$$

Following [Barrero, Bloom and Wright \(2017\)](#), I split firms into two groups according to median and define a high leverage firm if it is below the median and a low leverage firm otherwise. [Table 3.8](#) displays the results. Column (1) and (3) show the results for baseline regression for high leverage firms and low leverage firms, respectively. The high leverage firms are positively related with profit uncertainty since the coefficient of uncertainty for high leverage firms is positive and statistically significant. The coefficient of uncertainty for low leverage firms is statistically insignificant and lower than the coefficient of uncertainty for high leverage firms. The result implies that high leverage firms accumulate the inventories under higher uncertainty. Firms with high leverage or high levels of debt relative to assets might be forward looking and risk taker firms. So, firms' forward-looking investment decisions force them to increase inventory stocks under higher uncertainty for risky ventures.

In addition, I regress the baseline model augmented with an interaction term of uncertainty and liquidity. Column (2) and (4) shows the results for high leverage and

low leverage firms, respectively. The coefficients of interaction term and uncertainty are positive and statistically significant for high leverage firms but these coefficients are statistically insignificant for low leverage firms. This explains that profit uncertainty has direct effects on high leverage firms and also indirect effects via cash stocks. Overall, the findings suggest that high leverage firms accumulate the inventories even in the tightened financial constraints. However, low leverage firms do not appear to increase inventories under profit uncertainty.

3.5 Robustness check

In this section, I perform a variety of checks to show the robustness of my findings. I consider additional control variable to estimate the profit function and endogeneity problems for these checks.

3.5.1 Additional control variable

I include selling, general and administrative expenses variable scaled by beginning period of the total assets to control labor related information in the profit function (equation 3.3.2) since the expenses includes the labor/staff expenses. I follow the same process as in section 3.3.2 to generate profit uncertainty with additional control variable. Table 3.9 displays the results. Column (1) shows the results for baseline specification. The coefficient of uncertainty variable is 0.0997 and it is statistically significant. This results is similar to the results in section 3.4.2 Column (2). Since the hypothesis is rejected for third-order serial correlation at only 5 percent level, I also

consider one more lag of sales growth and estimate the model. Column (2) shows the results. The coefficient of uncertainty is 0.0775 and statistically significant. So this result is consistent with previous results while not considering the additional control variable in generating uncertainty variable.

3.5.2 Endogeneity

Next, I consider that liquidity is endogenous variable as it may be informative for other factors that affect the inventory behavior since the financial constraints are important for firms' inventory investment. [Kashyap, Lamont and Stein \(1994\)](#) argue that liquidity may be endogenous since firms are more innovative with higher liquidity. To deal with this issue, I consider that lagged value of inventory growth and liquidity are endogenous and other variables are exogenous. I then estimate the equation (3.3.1), using first-difference GMM two-step estimation. I use three and further lags of endogenous variables as instruments.

[Table 3.10](#) displays the results for baseline investment growth model for full sample and split samples, based on both firm size and bond ratings. Column (1) shows that inventory investment growth is positively related with higher uncertainty, which result is consistent in [Table 3.4](#) (Column 2) while not considering liquidity as endogenous. Column (2) and (3) display the results for size-based financial constrained and unconstrained firms, respectively. For constrained firms, the coefficient of uncertainty is positive but statistically insignificant at 10% level. However, the unconstrained firm is positively related with higher uncertainty since the coefficient of uncertainty

is positive and statistically significant.

Column (4) and (5) display the results for constrained and unconstrained firms based on bond ratings, respectively. The inventory growth are positively associated with high uncertainty for both types of firms since the coefficient of uncertainty is positive and statistically significant for both types of firms. However, the coefficient of uncertainty for constrained firms is lower than for unconstrained firms. These results are consistent with the results considering liquidity as exogenous in [Table 3.4](#).

For all these estimation, I perform the Hansen J and AR tests for the validity of the instruments. Hansen J test of over-identifying restrictions does not reject this specification at 10% level except in (3), and the hypothesis that there is no significant evidence of third-order serial correlation in the first-differenced residuals is not rejected at 10% level except in Column (1) and (3). Thus, the the finding suggests that results are consistent, considering liquidity as endogenous variable.

In addition, one might argue that uncertainty variable is endogenous since it could be a reverse causality. For example, more inventory holdings could make firms more volatile. To deal with issue, I employ first-difference GMM two-step estimation, considering all variables as endogenous variables and use three to six lags of the regressors (except of uncertainty) are used as instruments. I use one to four lags for uncertainty variables as instrument variables. I show the baseline results in [Table 3.11](#). Column (1) and (2) show that the coefficient of uncertainty is positive and statistically significant. This results implies that US firms hold more inventory stocks under higher uncertainty. So this results are consistent with the results, while not considering the uncertainty and other variable as endogenous in [Table 3.4](#).

3.6 Conclusion

Though the effect of uncertainty on firms' capital investment has been extensively studied in the literature, the effects of such uncertainty on firm's inventory investment is unclear. My paper fills this gap. I examine the effect of idiosyncratic profit uncertainty on US manufacturing firms' inventory investment, using an unbalanced panel data for 1981–2017. More specifically, I empirically investigate the effects of profit uncertainty on firms' inventory investment in the presence of asymmetric information. I use a new approach to construct yearly firm-level idiosyncratic uncertainty based on profit function, using standard deviation within a year from a large quarterly data. I find that US manufacturing firms increase their inventory stocks significantly for precautionary motive to avoid running out of stocks under higher profit uncertainty. I also find that each component (i.e. raw materials, work-in-progress and finished goods) of inventory investment is positively driven by higher uncertainty. Small firms do not appear to increase inventory stocks under higher uncertainty. Lending channel has little effect on inventory investment since the bank dependent firms also increase inventory stocks when profit uncertainty exists. Remarkably, high leverage firms increase the inventory investment even though they face tightened financial constraints. The findings suggest that firm's characteristics is an important mechanism through which uncertainty affects inventory investment over the business cycle.

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Table 3.2: Descriptive statistics: Total observations

Variables	Observation	Mean	S.D	Min	25p	Median	75p	Max
σ_{it}	60857	0.169	0.103	0.000	0.102	0.148	0.210	1.507
ΔI_{it}	60857	0.040	0.373	-5.696	-0.105	0.031	0.173	5.694
ΔS_{it}	60857	0.048	0.287	-4.836	-0.056	0.042	0.149	7.021
$I_{it} - S_{it}$	60857	-1.972	0.677	-7.814	-2.308	-1.917	-1.554	2.806
LIQ_{it}	60857	0.177	0.286	-0.002	0.026	0.089	0.234	11.040

Note: The sample period is 1981–2017. The sample covers the US public manufacturing firms (SIC code 2000–3999) from Compustat. The definition of the variables are in [Table 3.1](#).

Table 3.3: Descriptive statistics

Variables	Mean	S.D.	Min	25p	Median	75p	Max	Mean	S.D.	Min	25p	Median	75p	Max
A. Firm size														
1. Small					2. Large									
σ_{it}	0.184	0.110	0.001	0.112	0.162	0.228	1.507	0.154	0.093	0.000	0.093	0.135	0.191	1.491
ΔI_{it}	0.032	0.434	-5.696	-0.138	0.028	0.202	5.694	0.049	0.299	-3.189	-0.078	0.033	0.150	5.112
ΔS_{it}	0.043	0.334	-4.836	-0.079	0.043	0.169	7.021	0.053	0.230	-3.368	-0.038	0.042	0.131	3.434
$I_{it} - S_{it}$	-1.865	0.718	-7.814	-2.217	-1.797	-1.420	2.806	-2.078	0.616	-7.265	-2.372	-2.017	-1.691	0.783
LQ_{it}	0.212	0.320	0.000	0.025	0.110	0.295	10.108	0.143	0.241	-0.002	0.026	0.076	0.183	11.040
B. Bond rating														
3. Bank-dependent					4. Bond-rated									
σ_{it}	0.178	0.112	0.000	0.105	0.155	0.222	1.507	0.164	0.097	0.002	0.100	0.144	0.204	1.464
ΔI_{it}	0.034	0.382	-5.696	-0.116	0.026	0.173	5.353	0.044	0.367	-5.444	-0.098	0.033	0.173	5.694
ΔS_{it}	0.044	0.295	-4.167	-0.067	0.040	0.152	7.021	0.050	0.282	-4.836	-0.050	0.044	0.146	4.001
$I_{it} - S_{it}$	-1.939	0.664	-7.177	-2.278	-1.888	-1.524	2.038	-1.990	0.684	-7.814	-2.324	-1.935	-1.571	2.806
LQ_{it}	0.155	0.259	-0.002	0.022	0.074	0.198	7.387	0.190	0.299	0.000	0.029	0.099	0.253	11.040

Note: The sample period is 1981–2017. In Panel (A), I define a small firm if the firm is below the median of the total assets of total observations and a large firm if the firm is above the median. The observations for small firms and large firms are 30,428 and 30,429, respectively. In Panel (B), I define a bank-dependent firm if the firm that do not have a bond ratings from Standard and Poors at the beginning of the year and, a bond-rated firm otherwise. The total observations for bank-dependent and bond rated are 22,275 and 38,582, respectively. The sample covers US public manufacturing firms (SIC code 2000–3999). The definition of the variables are in [Table 3.1](#).

Table 3.4: Baseline results: Effect of uncertainty for inventory investment growth

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ΔI_{it-1}	-0.270*** (0.0396)	-0.269*** (0.0396)	-0.274*** (0.0393)	-0.287*** (0.0437)	-0.269*** (0.0396)	-0.287*** (0.0437)
ΔS_{it}	0.786*** (0.0153)	0.785*** (0.0153)	0.783*** (0.0156)	0.798*** (0.0149)	0.785*** (0.0152)	0.794*** (0.0146)
ΔS_{it-1}	0.0534* (0.0292)	0.0533* (0.0292)	0.0571** (0.0288)	0.0629** (0.0318)	0.0535* (0.0292)	0.0626** (0.0318)
$I_{it-1} - S_{it-1}$	-0.875*** (0.0490)	-0.875*** (0.0490)	-0.868*** (0.0488)	-0.853*** (0.0536)	-0.875*** (0.0490)	-0.851*** (0.0536)
LIQ_{it}	-0.141*** (0.0160)	-0.141*** (0.0159)		-0.138*** (0.0178)	-0.148*** (0.0241)	-0.149*** (0.0243)
σ_{it}		0.117*** (0.0208)	0.119*** (0.0207)	0.109*** (0.0200)	0.110*** (0.0225)	0.102*** (0.0224)
CF_{it}			-0.0323 (0.0207)	-0.0276 (0.0183)		
COV_{it}				0.0008 (0.0001)		0.0001 (0.0001)
$\sigma_{it} \times LIQ_{it}$					0.0330 (0.0952)	0.0455 (0.0927)
$\sigma_{it} \times COV_{it}$						0.0038 (0.0008)
<i>Observations</i>	50858	50858	49785	47109	50858	47109
<i>AR2 (p)</i>	0.000	0.000	0.000	0.000	0.000	0.000
<i>AR3 (p)</i>	0.061	0.060	0.039	0.049	0.060	0.050
<i>Hansen (p)</i>	0.178	0.182	0.404	0.288	0.181	0.298

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.5: Results: Effects of uncertainty for components of inventory investment growth

	Total	Raw materials		Work-in-progress		Finished goods	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔI_{it-1}	-0.246*** (0.0563)	-0.644 (0.401)	-0.645 (0.400)	-1.343*** (0.205)	-1.341*** (0.204)	-1.079*** (0.311)	-1.082*** (0.309)
ΔS_{it}	0.729*** (0.0257)	0.618*** (0.0960)	0.618*** (0.0959)	0.800*** (0.0680)	0.800*** (0.0678)	0.683*** (0.0626)	0.684*** (0.0629)
ΔS_{it-1}	-0.00975 (0.0355)	0.354 (0.297)	0.355 (0.296)	0.887*** (0.175)	0.886*** (0.174)	0.698*** (0.214)	0.700*** (0.213)
$I_{it-1} - S_{it-1}$	-0.880*** (0.0721)	-0.402 (0.303)	-0.403 (0.303)	-1.164*** (0.205)	-1.161*** (0.204)	-0.809*** (0.286)	-0.811*** (0.284)
LIQ_{it}	-0.105*** (0.0305)	-0.151** (0.0730)	-0.143 (0.0912)	-0.194** (0.0890)	-0.133 (0.143)	-0.399*** (0.0726)	-0.353*** (0.0913)
σ_{it}	0.183*** (0.0363)	0.238*** (0.0654)	0.246*** (0.0814)	0.205** (0.0837)	0.271** (0.116)	0.192** (0.0799)	0.240*** (0.0837)
$\sigma_{it} \times LIQ_{it}$			-0.0471 (0.350)		-0.390 (0.512)		-0.297 (0.499)
<i>Observations</i>	14860	8879	8879	8484	8484	8948	8948
<i>AR2 (p)</i>	0.000	0.177	0.176	0.000	0.000	0.012	0.011
<i>AR3 (p)</i>	0.977	0.210	0.210	0.781	0.787	0.490	0.495
<i>Hansen (p)</i>	0.172	0.526	0.525	0.426	0.416	0.376	0.383

Note: The sample period is 2004–2017. Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.6: Results: Effects of uncertainty for inventory investment growth

Variables	A. Small		B. Large	
	(1)	(2)	(3)	(4)
ΔI_{it-1}	-0.238*** (0.0570)	-0.238*** (0.0569)	-0.317*** (0.0472)	-0.315*** (0.0473)
ΔS_{it}	0.732*** (0.0227)	0.732*** (0.0226)	0.871*** (0.0158)	0.871*** (0.0157)
ΔS_{it-1}	0.00349 (0.0398)	0.00328 (0.0397)	0.135*** (0.0364)	0.134*** (0.0365)
$I_{it-1} - S_{it-1}$	-0.893*** (0.0692)	-0.893*** (0.0692)	-0.830*** (0.0594)	-0.832*** (0.0595)
LIQ_{it}	-0.146*** (0.0205)	-0.141*** (0.0332)	-0.135*** (0.0213)	-0.183*** (0.0314)
σ_{it}	0.0380 (0.0340)	0.0424 (0.0372)	0.175*** (0.0204)	0.133*** (0.0236)
$\sigma_{it} \times LIQ_{it}$		-0.0195 (0.123)		0.273** (0.122)
<i>Observations</i>	23805	23805	27053	27053
<i>AR2 (p)</i>	0.000	0.000	0.000	0.000
<i>AR3 (p)</i>	0.270	0.271	0.001	0.001
<i>Hansen (p)</i>	0.415	0.414	0.107	0.092

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.7: Results: Effects of uncertainty for inventory investment growth

Variables	A. Bank-dependent		B. Bond-rated	
	(1)	(2)	(3)	(4)
ΔI_{it-1}	-0.418*** (0.0614)	-0.418*** (0.0612)	-0.206*** (0.0537)	-0.206*** (0.0537)
ΔS_{it}	0.811*** (0.0247)	0.810*** (0.0245)	0.764*** (0.0191)	0.764*** (0.0191)
ΔS_{it-1}	0.183*** (0.0450)	0.183*** (0.0447)	-0.00379 (0.0388)	-0.00367 (0.0388)
$I_{it-1} - S_{it-1}$	-0.714*** (0.0754)	-0.715*** (0.0752)	-0.940*** (0.0670)	-0.940*** (0.0670)
LIQ_{it}	-0.164*** (0.0297)	-0.189*** (0.0528)	-0.129*** (0.0175)	-0.126*** (0.0267)
σ_{it}	0.105*** (0.0325)	0.0878** (0.0409)	0.114*** (0.0267)	0.115*** (0.0281)
$\sigma_{it} \times LIQ_{it}$		0.123 (0.241)		-0.0130 (0.108)
<i>Observations</i>	16892	16892	33966	33966
<i>AR2 (p)</i>	0.000	0.000	0.000	0.000
<i>AR3 (p)</i>	0.072	0.072	0.185	0.186
<i>Hansen (p)</i>	0.083	0.082	0.251	0.252

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.8: Results: Uncertainty and leverage

Variables	A. High leverage		B. Low leverage	
	(1)	(2)	(3)	(4)
ΔI_{it-1}	-0.260*** (0.0629)	-0.259*** (0.0629)	-0.252*** (0.0558)	-0.252*** (0.0557)
ΔS_{it}	0.879*** (0.0176)	0.878*** (0.0176)	0.706*** (0.0215)	0.706*** (0.0214)
ΔS_{it-1}	0.0865* (0.0460)	0.0858* (0.0460)	0.00925 (0.0414)	0.00911 (0.0413)
$I_{it-1} - S_{it-1}$	-0.908*** (0.0845)	-0.910*** (0.0845)	-0.874*** (0.0682)	-0.874*** (0.0681)
LIQ_{it}	-0.0996*** (0.0203)	-0.158*** (0.0381)	-0.168*** (0.0207)	-0.157*** (0.0300)
σ_{it}	0.160*** (0.0241)	0.130*** (0.0243)	0.0373 (0.0324)	0.0504 (0.0395)
$\sigma_{it} \times LIQ_{it}$		0.229* (0.131)		-0.0542 (0.126)
<i>Observations</i>	25463	25463	25395	25395
<i>AR2 (p)</i>	0.000	0.000	0.000	0.000
<i>AR3 (p)</i>	0.083	0.086	0.904	0.905
<i>Hansen (p)</i>	0.092	0.087	0.101	0.101

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.9: Robustness: Effects of uncertainty for inventory investment growth

Variables	(1)	(2)
ΔI_{it-1}	-0.300*** (0.0907)	-0.250 (0.154)
ΔS_{it}	0.772*** (0.0218)	0.782*** (0.0380)
ΔS_{it-1}	0.0870** (0.0365)	0.0441 (0.0726)
ΔS_{it-2}		0.0424 (0.0655)
$I_{it-1} - S_{it-1}$	-0.798*** (0.0707)	-0.898*** (0.182)
LIQ_{it}	-0.122*** (0.0411)	-0.136*** (0.0186)
σ_{it}	0.0997*** (0.0313)	0.0775*** (0.0291)
<i>Observations</i>	30764	27250
<i>AR2</i> (<i>p</i>)	0.000	0.018
<i>AR3</i> (<i>p</i>)	0.054	0.903
<i>Hansen</i> (<i>p</i>)	0.524	0.101

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.10: Robustness: Liquidity as a endogenous variable

	Baseline	Small	Large	Bank-dependent	Bond-rated
Variables	(1)	(2)	(3)	(4)	(5)
ΔI_{it-1}	-0.252*** (0.0397)	-0.218*** (0.0535)	-0.249*** (0.0431)	-0.371*** (0.0656)	-0.190*** (0.0516)
ΔS_{it}	0.761*** (0.0177)	0.716*** (0.0230)	0.869*** (0.0174)	0.801*** (0.0312)	0.741*** (0.0201)
ΔS_{it-1}	0.0443 (0.0289)	-0.00546 (0.0371)	0.0899*** (0.0343)	0.149*** (0.0460)	-0.0125 (0.0372)
$I_{it-1} - S_{it-1}$	-0.883*** (0.0508)	-0.909*** (0.0658)	-0.912*** (0.0555)	-0.751*** (0.0865)	-0.949*** (0.0656)
LIQ_{it}	0.312** (0.141)	0.155 (0.119)	-0.0633 (0.127)	0.368 (0.295)	0.232* (0.130)
σ_{it}	0.126*** (0.0213)	0.0371 (0.0336)	0.173*** (0.0206)	0.0965*** (0.0353)	0.133*** (0.0277)
<i>Observations</i>	50858	23805	27053	16892	33966
<i>AR2 (p)</i>	0.000	0.000	0.000	0.000	0.000
<i>AR3 (p)</i>	0.068	0.281	0.019	0.198	0.180
<i>Hansen (p)</i>	0.245	0.433	0.086	0.116	0.201

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.11: Robustness: All variables as endogenous variables

Variables	(1)	(2)
ΔI_{it-1}	-0.150 (0.112)	0.00374 (0.0889)
ΔS_{it}	0.728*** (0.124)	0.895*** (0.110)
ΔS_{it-1}	-0.0414 (0.0645)	0.0643 (0.0593)
ΔS_{it-2}	0.0447*** (0.0164)	0.0191 (0.0134)
$I_{it-1} - S_{it-1}$	-0.321*** (0.0585)	-0.371*** (0.0608)
LIQ_{it}	0.566*** (0.214)	
CF_{it}		-0.0641 (0.200)
σ_{it}	0.154*** (0.0406)	0.139*** (0.0347)
<i>Observations</i>	46330	45341
<i>AR2</i> (p)	0.019	0.006
<i>AR3</i> (p)	0.108	0.127
<i>Hansen</i> (p)	0.102	0.092

Note: Two-step first-difference GMM estimate coefficients and robust standard errors to autocorrelation and heteroscedasticity are reported. I consider all variables as endogenous variables and use three to six lags of the regressors (except of uncertainty) as instruments and one to four lags of uncertainty variables as instruments. The AR2 (AR3) is a test for second- (third-) order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation, using a Lagrange multiplier test [Arellano and Bond \(1991\)](#). Instrument validity is tested using a Hansen test of the over-identifying restrictions. * $p < .1$, ** $p < .05$, *** $p < .01$

Appendix A

Appendix for Chapter 1

A.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).¹ 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.

¹<http://www.ism.ws/ISMReport/MfgROB.cfm?navItemNumber=12942>

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:

$$R_t = (i/100) - \log(\text{Price index of } GDP_{t+1} / \text{Price index of } GDP_t) \quad (\text{A.1.1})$$

, where, R is the real lending rate.

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:

$$CC_t = (R_t + DEP_t)(\text{Price index of } TBI_t / \text{Price index of } GDP_t) \quad (\text{A.1.2})$$

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.²

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.

A.2 Baseline model results

As a preliminary step, we estimate the baseline model and find that lagged values of dependent variables and other independent variables have predictive power for business investment growth and its components. Table 1.14 shows the sum of coefficient on the lags of each explanatory variables and p -values for the joint significance of the lags of each variables. Most of the variables have expected positive sign and are

²<https://finance.yahoo.com/q/hp?s=%5EGSPC+Historical+Prices>.

statistically significant.

A.3 SR calculation

The calculation of SR is as:

$$SR = \frac{\hat{g}^{uu} + \hat{g}^{dd}}{\hat{g}^{uu} + \hat{g}^{du} + \hat{g}^{ud} + \hat{g}^{dd}}, \quad (\text{A.3.1})$$

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

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

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

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

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

A.4 Additional models for downturns and direction of investment

[Table 1.15](#) 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 1.16](#) shows the results. Panel (a) shows that BCI-nested model is better than BCI non-nested model for 1 and 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.

A.5 Additional Figures

[Figure A.1](#) shows the relationship between BCI and ΔTBI (and its components) over the period 1955Q1–2016Q4. Panel (a) displays the close movements between ΔTBI

Figure A.1: Correlations: BCI with business investment growth and its components

Notes: The NBER recession dates are in grey shading.

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 A.2: Cross-correlations: BCI with business investment growth and its components

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.6 Additional Tables

Table A.1: Unit root tests

Variables	ADF	PP	Variables	ADF	PP
BCI	-6.007**	-5.997**	Δ TBI	-5.717**	-7.095**
TBI	-0.817	-1.203	Δ SI	-6.235**	-10.279**
SI	-2.244	-2.398	Δ EI	-5.896**	-8.748**
EI	-0.908	-0.919	Δ IPI	-3.376**	-3.872**
IPI	-1.569	-2.385	Δ GDP	-4.617**	-7.875**
GDP	-1.758	-2.053	Δ CC	-6.511**	-14.801**
CC	-1.302	-1.061	Δ SP	-11.034**	-14.033**
SP	-0.405	-0.550	Δ CF	-6.693**	-15.989**
CF	-1.075	-1.082			
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 A.2: Bi-variate Granger-causality Wald tests

Explained variables	Explanatory variables	Chi-squared	<i>p</i> -value	Granger-causality
ΔTBI	BCI	73.746	.000	BCI $\rightarrow \Delta\text{TBI}$
BCI	ΔTBI	2.200	.333	$\Delta\text{TBI} \nrightarrow \text{BCI}$
ΔSI	BCI	31.598	.000	BCI $\rightarrow \Delta\text{SI}$
BCI	ΔSI	1.781	.410	$\Delta\text{SI} \nrightarrow \text{BCI}$
ΔEI	BCI	77.989	.000	BCI $\rightarrow \Delta\text{EI}$
BCI	ΔEI	4.474	.346	$\Delta\text{EI} \nrightarrow \text{BCI}$
ΔIPI	BCI	10.304	.036	BCI $\rightarrow \Delta\text{IPI}$
BCI	ΔIPI	2.701	.609	$\Delta\text{IPI} \nrightarrow \text{BCI}$

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

Table A.3: Multivariate model: Granger-causality Wald tests

Explained variables	Explanatory variables	Chi-squared	<i>p</i> -value	Granger-causality
ΔTBI	BCI	37.313	.000	BCI $\rightarrow \Delta\text{TBI}$
BCI	ΔTBI	3.096	.213	$\Delta\text{TBI} \nrightarrow \text{BCI}$
ΔSI	BCI	13.824	.001	BCI $\rightarrow \Delta\text{SI}$
BCI	ΔSI	1.361	.506	$\Delta\text{SI} \nrightarrow \text{BCI}$
ΔEI	BCI	36.180	.000	BCI $\rightarrow \Delta\text{EI}$
BCI	ΔEI	3.222	.200	$\Delta\text{EI} \nrightarrow \text{BCI}$
ΔIPI	BCI	7.067	.132	$\text{BCI} \nrightarrow \Delta\text{IPI}$
BCI	ΔIPI	3.780	.437	$\Delta\text{IPI} \nrightarrow \text{BCI}$

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

Table A.4: OOS results using rolling window method: Predictive ability of BCI for investment growth

Category of investment	R_{OS}^2	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_{OS}^2 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 $R_{OS}^2 \leq 0$ against $R_{OS}^2 > 0$. *** Corresponds with statistical significance at the 1% level, ** 5% level, * 10% level.

Appendix B

Appendix for Chapter 2

B.1 Construction of household investment

To construct Household Investment (HI) series, we use the following BEA's chain aggregation method:

We normalize $HI_T = 1$, where T is reference date and set $T = 1$. Then we set $HI_t = HI_{t-1} \times Q_t$, where Q_t is Fisher Index.

$$Q_t = \sqrt{\frac{P_{t-1}^{DG} DG_t + P_{t-1}^{RI} RI_t}{P_{t-1}^{DG} DG_{t-1} + P_{t-1}^{RI} RI_{t-1}}} \times \frac{P_t^{DG} DG_t + P_t^{RI} RI_t}{P_t^{DG} DG_{t-1} + P_t^{RI} RI_{t-1}}$$

where,

DG = Durable goods

RI = Residential investment

P^{DG} = Price index of durable goods

P^{RI} = Price index of residential investment

B.2 Index of consumer sentiment

We collect consumer confidence data from Surveys of Consumers, University of Michigan. We focus on the Index of Consumer Sentiment (ICS) and Index of Consumer Expectations (ICE), which are based on the following five questions:

- Q_1 . We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?
- Q_2 . Now looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?
- Q_3 . Now turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have good times financially, or bad times, or what?
- Q_4 . Looking ahead, which would you say is more likely—that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?
- Q_5 . About the big things people buy for their homes—such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?

$$ICS = \frac{Q_1 + Q_2 + Q_3 + Q_4 + Q_5}{6.7558} + 2.0$$

$$ICE = \frac{Q_2 + Q_3 + Q_4}{4.1134} + 2.0$$

B.3 Support documents

Table B.1: Cross-correlations: Household investment in t with a Variable in $t + j$

Variable	Rel Std.	$j = -4$	-3	-2	-1	0	1	2	3	4
(a) 1947Q1–2017Q4										
Business Investment	1.419	-0.423	-0.322	-0.135	0.105	0.380	0.568	0.660	0.671	0.619
Output	4.057	-0.312	-0.156	0.079	0.340	0.584	0.678	0.659	0.564	0.447
(b) 1947Q1–1983Q4										
Business Investment	1.682	-0.597	-0.542	-0.352	-0.061	0.300	0.533	0.633	0.624	0.544
Output	4.130	-0.483	-0.339	-0.076	0.228	0.525	0.613	0.568	0.438	0.297
(c) 1984Q1–2017Q4										
Business Investment	1.018	-0.170	-0.023	0.130	0.280	0.437	0.542	0.611	0.651	0.653
Output	4.210	-0.011	0.146	0.329	0.510	0.676	0.733	0.722	0.669	0.599

Note: We take log in level and de-trend with the HP-filter ($\lambda = 1600$). The largest correlations are shown in bold.

Table B.2: Cross-correlations: Household Investment in t with a Variable in $t + j$

Variable	Rel Std.	$j = -4$	-3	-2	-1	0	1	2	3	4
(a) 1947Q1–2017Q4										
Business Investment	1.380	-0.180	-0.074	0.068	0.229	0.422	0.517	0.587	0.642	0.650
Output	4.090	0.042	0.199	0.353	0.517	0.670	0.725	0.729	0.713	0.672
(b) 1947Q1–1983Q4										
Business investment	1.387	-0.305	-0.212	-0.072	0.114	0.337	0.495	0.607	0.677	0.695
Output	3.524	-0.121	-0.003	0.154	0.331	0.516	0.597	0.621	0.614	0.569
(c) 1984Q1–2017Q4										
Business Investment	1.060	-0.059	0.033	0.150	0.268	0.401	0.464	0.503	0.564	0.572
Output	4.125	0.053	0.162	0.316	0.485	0.644	0.689	0.685	0.669	0.656

Note: We take log in level and de-trend with Hamilton filter. The largest correlations are shown in bold.

Table B.3: Cross-correlations: Components of residential investment in t with output in $t + j$

	Rel Std.	$j = -4$	-3	-2	-1	0	1	2	3	4
(a) 1958Q1–2017Q4										
Single family	9.525	-0.228	-0.059	0.174	0.425	0.635	0.731	0.730	0.670	0.590
Multi family	12.438	0.220	0.313	0.399	0.457	0.469	0.417	0.327	0.218	0.117
Other structures	3.995	-0.079	0.048	0.163	0.313	0.509	0.617	0.593	0.532	0.469
(b) 1958Q1–1983Q4										
Single family	9.538	-0.389	-0.226	0.035	0.340	0.620	0.705	0.662	0.550	0.433
Multi family	12.328	-0.008	0.132	0.294	0.440	0.523	0.480	0.369	0.223	0.087
Other structures	3.810	-0.234	-0.101	0.028	0.216	0.476	0.578	0.466	0.328	0.218
(c) 1984Q1–2017Q4										
Single family	10.955	-0.037	0.110	0.309	0.505	0.647	0.702	0.688	0.634	0.563
Multi family	14.780	0.611	0.617	0.561	0.466	0.361	0.241	0.1451	0.069	0.025
Other structures	4.575	-0.143	-0.031	0.088	0.231	0.413	0.522	0.601	0.632	0.647

Note: We take log in level and de-trend with HP-filter ($\lambda = 1600$). The largest correlations are shown in bold.

Table B.4: Multivariate model: Granger-causality Wald tests

Explained variables	Explanatory variables	Chi-squared	p -value	Granger-causality
Household investment	ICE	22.203	0.000	ICE $\rightarrow$ Household investment
Hours worked	ICE	9.2689	0.055	ICE $\nrightarrow$ Hours worked
Output	ICE	15.88	0.003	ICE $\rightarrow$ Output
ICE	Household investment	17.544	0.002	Household investment $\rightarrow$ ICE
ICE	Hours worked	4.803	0.308	Hours worked $\nrightarrow$ ICE
ICE	Output	9.440	0.051	Output $\nrightarrow$ ICE

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

Figure B.1: Cross-correlations: ICE and other variables (Hamilton Filter)

(a) ICE (t) and Household investment (t+j) (b) ICE (t) and Housing starts (t+j)

(c) ICE (t) and Output (t+j) (d) ICE (t) and Hours worked (t+j)

(e) ICE (t) and Business investment (t+j)

Note: All series (except ICE) are logged and de-trended with the Hamilton-filter. The sample period is 1960Q1 to 2017Q4.

Note: These are IRFs to confidence shocks in four-variables VAR with two alternative measures of confidence: ICE and ICS. Confidence is ordered in first in both cases. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure B 2: Responses to a one standard deviation consumer confidence shock

Note: These are IRFs from a four-variables VAR with ICE (ordered first), household investment, labour force participation rate and output. The solid lines are actual impulse responses. The grey shaded areas are one standard error confidence bands constructed using the bias-corrected bootstrap after bootstrap procedure in [Kilian \(1998\)](#). The sample period is 1960Q1 to 2017Q4.

Figure B.4: Cross-correlations: ICE (t) with durable goods (industrial production) ($t + j$)

Note: Durable goods (industrial production) series are logged and de-trended with the HP-filter ($\lambda = 1600$).

Appendix C

Appendix for Chapter 3

C.1 Inventory investment model

I follow a stock adjustment model from [Lovell \(1961\)](#) to investigate the effect of profit uncertainty on inventory investment, empirically. The inventory investment growth model is as follows:

$$\Delta I_{it} = \theta_1(I_{it}^* - I_{it}) - \theta_2(S_{it} - E_{t-1}S_{it}) + \epsilon_{it} \quad (\text{C.1.1})$$

where, ΔI_{it} is the change in inventory stocks for firm i in year t that depends on the two components. The first component, planned or anticipated inventory investment, depends on the gap between actual inventory (I_{it}) and “desired” inventory (I_{it}^*). The second is the unanticipated inventory investment—the gap between actual sales (S_{it}) and expected sales ($E_{t-1}S_t$)—that captures the extent to which inventories buffer sales surprises. The term, ϵ_{it} , is the idiosyncratic error term. To find a determinant

of I_{it}^* , I use [Blinder and Maccini \(1991\)](#) approach as follows:

$$I_{it}^* = \beta_i + \beta_1 E_{t-1} S_{it} + w_{it}, \quad (\text{C.1.2})$$

where, β_i and w_{it} represent firm's fixed effect and idiosyncratic error term, respectively. The expected sales, $E_{t-1} S_{it}$ follows an autoregressive process as in [Blinder \(1986\)](#):

$$E_{t-1} S_{it} = \delta_i + \delta_1 S_{it-1} + \delta_2 S_{it-2} + v_{it}, \quad (\text{C.1.3})$$

where, δ_i and v_{it} denote firm's fixed effects and idiosyncratic errors for the expected sales function. Substituting equations (C.1.2) and (C.1.3) into inventory investment equation (C.1.1) yields the following regression equation:

$$\Delta I_{it} = -\theta_1 I_{it} - \theta_2 S_{it} + \theta_3 S_{it-1} + \theta_4 S_{it-2} + \mu_i + \varepsilon_{it}, \quad (\text{C.1.4})$$

where,

$$\theta_3 = (\theta_1 \beta_1 - \theta_2) \delta_1, \quad (\text{C.1.5})$$

$$\theta_4 = (\theta_1 \beta_1 - \theta_2) \delta_2, \quad (\text{C.1.6})$$

$$\mu_i = (\theta_1 \beta_1 - \theta_2) \delta_i + \theta_1 \beta_i, \text{ and} \quad (\text{C.1.7})$$

$$\varepsilon_{it} = (\theta_1\beta_1 - \theta_2)v_{it} + \theta_1w_{it} + \epsilon_{it}. \tag{C.1.8}$$