

ON THE EFFECTS OF CONFIDENCE AND UNCERTAINTY ON AGGREGATE DEMAND: EVIDENCE FROM CHILE*

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"[E]conomic prosperity is excessively dependent on a political and social atmosphere which is congenial to the average businessman. If the fear of a Labour Government or a New Deal depresses enterprise, this need not be the result either of a reasonable calculation or of a plot with political intent; it is the mere consequence of upsetting the delicate balance of spontaneous optimism. In estimating the prospects of investment, we must have regard, therefore, to the nerves and hysteria and even the digestions and reactions to the weather of those upon whose spontaneous activity it largely depends."

John Maynard Keynes (1936)

The state of long-term expectation, upon which our [investment] decisions are based, does not solely depend, therefore on the most probable forecast we can make. It also depends on the confidence with which we make this forecast-on how highly we rate the likelihood of our best forecast turning out quite wrong.

John Maynard Keynes (1936)

I. INTRODUCTION

Confidence indicators play a prominent role in explaining contingent economic developments. These indicators are useful to understand the context, or atmosphere referred by Keynes, in which economic decisions are taken.

The objective of this paper is to analyze the effects of entrepreneurs and consumers' confidence on investment and consumption in Chile using a new

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data set of confidence indicators.¹ Following Nowzohour and Stracca (2017), two aspects of sentiments are important for this study: (i) confidence levels; and (ii) dispersion measures calculated from responses recorded in the confidence database (uncertainty).

Confidence indicators

Ample literature documents empirically that confidence indicators lead economic activity measures (see Chanut and Medel, 2018, for the case of Chile). This predictability property can potentially be exploited to get more accurate forecasts. However, the subjective nature of confidence measures raises concerns about the robustness of such empirical correlations. An example will help to understand the general idea. When a given economy is booming, typically we find that entrepreneurs and consumers entertain optimistic views of their business and income, confidence indicators improve and private expenditure is dynamic. The opposite happens in a depression. There are exceptions, of course, where the evolution of private spending does not exactly follow confidence measures, for a variety of reasons.

In standard macroeconomic theory, we find no clear definition of confidence as a variable, neither a fundamental role is assigned to it. More specifically, in standard New Keynesian models, fluctuations in investment are determined by changes in the marginal productivity of capital, changes in relative prices of investment goods, adjustment costs to install capital, etc. (i.e. the effective user costs of capital). When taken to investment data, traditional stylized macroeconomic models are not able to explain certain episodes reasonably. In these situations, experts' judgement can be informed by the level of entrepreneurs' confidence indicators.

Uncertainty

A recent study by Drobetz et al. (2017) finds that the strength of the negative relation between investment and the cost of capital decreases in times of high economic policy uncertainty. Therefore, we use direct or firm level responses to survey questions to construct synthetic confidence indicators as well as to get measures of the dispersions of responses. Regarding the latter, Bachmann et al. (2013), suggest that is a good proxy of uncertainty. The intuition is that in periods of high uncertainty business managers tend to postpone projects and to halt investment expenses. Thus, increasing the amount of dispersion.

Empirical strategy and main results

To support the dynamic analysis that we will develop in section III below, we start by exploring simple correlations in the data. We construct synthetic confidence indicators with responses from entrepreneurs (IMCE database). Analogously,

¹ Gross fixed capital formation (GFCF) is used as proxy of investment.



we study the behavior of consumption and consumers' confidence indicators (IPEC database). We ask whether confidence has the capacity to anticipate, in a predictive sense, the behavior of investment and consumption.² Similarly, whether an increase in uncertainty, understood as an increase in the dispersion responses, significantly postpones spending on consumption and investment.

Next, we study more formally the joint dynamics and propagation of investment and consumption resulting from several shocks. We have special interest on confidence and uncertainty shocks. In particular, we specify structural VAR models (SVAR) for consumption and investment along with confidence and uncertainty variables. A motivation to develop this methodology is that results from these econometric models provide timely answers usually faster than traditional structural models.³

Finally, we illustrate with two empirical applications how these empirical models contribute to the macroeconomic analysis. The first application seeks to explain the investment cycle by contributions of key drivers (historical decomposition). The second application analyzes whether recent menaces of trade war between leading trading partners of Chile exert a negative influence on domestic confidence and thereby lead to less dynamic investment. These two applications were explained in boxes in the Monetary Policy Reports of June 2016 and September 2019, respectively.

We find that after a positive confidence shock, investment does not react on impact, but it exhibits a positive and persistent response in the 12 quarters following the shock. Private consumption shows a positive response on impact and returns to its trend level 8 quarters later. Uncertainty shocks generate a rapid slow-down and bounce-back in investment. Private consumption, instead, shows a weak negative response in the mid-term.

This paper uses the same survey data as Chanut, et al. (2018) and Figueroa and Pedersen (2019). However, likewise Albagli and Luttini (2015), we dig into specific questions aiming to anticipate investment better. Due to detailed focus on questions, we leave out the analysis responses taken from mining and construction sectors, whereas we concentrate on retail and manufacturing, whose questions on expected future sales/production levels are alike. Besides, we extend the analysis to examine microdata from consumers' surveys. In one extreme Chanut, et al. (2018) analyze all questions one by one and in the other Figueroa and Pedersen (2019) use published sentiment indicators data; we lay in between: we use synthetic confidence indices.

Regarding the methodology, these two papers and ours use simple Granger causality tests. The others focus on forecasting properties of confidence indicators, while we focus on policy applications, estimating SVAR models to get

² This paper follows to some extent the empirical strategy by Santero and Westerlund (1996).

³ The sample analyzed covers a period with a stable macroeconomic framework: inflation-targeting with exchange rate flexibility, an independent central bank and a fiscal policy that follows a fiscal rule.

historical decompositions, simulate impulse responses, and perform forecasting exercises. Finally, as in Albagli and Luttini (2015) and Cerda et al. (2018), we study shocks to the uncertainty measure, while the other papers in this volume do not analyze this issue.

The structure of this paper is as follows. In section II, we detail the construction of confidence and uncertainty measures, and study their cyclical properties in a bivariate analysis. In section III, we describe our main empirical setting, and discuss the effects of confidence and uncertainty shocks. Finally, in section IV we present some concluding remarks.

II. MEASURING CONFIDENCE AND UNCERTAINTY

To fix concepts, by confidence we refer to the answers to questions concerning average expected outcome for an activity variable. For instance, we will measure confidence about the future economic situation as the difference between the share of optimistic expectations and the share of pessimistic expectations. Uncertainty, instead, relates to the degree of agreement about that expected outcome. We say there is low uncertainty when agents' expectations are concentrated around a central scenario or, in other words, they share a common view, whether it be optimistic or pessimistic. Conversely, we say there is high uncertainty when agents' expectations are more dissimilar.

We construct confidence and uncertainty measures from entrepreneur and consumer surveys. In the next subsection, we briefly describe the characteristics of each survey and list the main questions we use. From these questions, we define confidence and uncertainty indicators for 'present,' 'future,' and 'nation-wide' economic outcomes. In the following subsection, we analyze some cyclical properties of these indicators.

1. Data Description

Business confidence and uncertainty: The IMCE survey

We build measures of business confidence and business uncertainty using data from the monthly business confidence survey, IMCE⁴. This survey asks entrepreneurs and business managers about their outlook for national and business-specific economic conditions, current and future perspectives, and other specific indicators such as production levels, inventories, demand, and employment. The sample contains around 600 firms from four sectors of the Chilean economy: retail, manufacturing, mining, and construction, which account for 35% of total GDP. The window period in which companies must respond to the survey is within the month.

⁴ IMCE: Indicador Mensual de Confianza Empresarial. The IMCE survey was initially developed in 2003 by the Central Bank of Chile and later outsourced to ICARE, a private organization, and Universidad Adolfo Ibáñez under a tender procedure.



Each question in the IMCE survey has three possible answers: 'favorable,' 'unfavorable,' or 'neutral.' We use the proportion of favorable and unfavorable answers to construct indicators of business confidence and business uncertainty. Let B denote the difference between the share of favorable and unfavorable answers:

B = % favorable - % unfavorable

Then, the *confidence* indicator is just a linear transformation of B such that this indicator ranges between 0 and 100, where a value of 0 means that 100% of the answers are unfavorable; a value of 100 means that 100% of the answers are favorable; and a value of 50 indicates that confidence is at a neutral or balanced level.

To construct uncertainty indicators, we follow Bachmann et al. (2013) and use the cross-sectional dispersion of answers, which is:

$$uncertainty = \sqrt{\% favorable + \% unfavorable - (\% favorable - \% unfavorable)^2} \cdot 100$$

So, for instance, if half the answers are favorable and the other half are unfavorable, there is maximum uncertainty, and our indicator is equal to 100. Contrariwise, if all the answers are favorable, or if all are unfavorable, our uncertainty indicator is equal to 0.

We group questions into three categories based on their content: 'present,' 'future,' and 'national,' and compute average confidence and uncertainty indicators for each category. We defined these categories based on the evidence we present in section II.4, where we analyze whether there is a meaningful relation between confidence and uncertainty indicators and aggregate demand variables.

Table 1 lists the questions used to generate our indicators. We focus on answers from the retail and manufacturing sectors (thus excluding the construction and mining sectors) for the following reasons. First, firms in the construction sector are not asked about present or future business-specific economic conditions. Second, we exclude the answers from firms in the mining sector, because these exhibit issues such as high volatility relative to the other sectors. Also, these questions present little correlation with domestic activity (see Figueroa and Pedersen (2019)).

Figure 1 presents the confidence and uncertainty indicators in the top left and right graphs, respectively. Confidence in the present and future situation

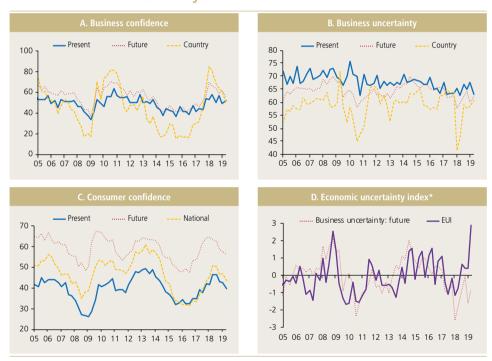
⁵ The norm is that firms' responses are equally important. The exception is the mining sector, where firms' responses present importance weighting. In effect, Codelco weighs 46%, Collahuasi weighs 6% and any other mining company weighs 1%. These weights will be normalized taking into account the total number of companies surveyed in each month. For example, if in a given month Codelco, Collahuasi and 10 other companies answered, the weighting of Codelco is $0.46 / (0.46 + 0.06 + 10 \times 0.01) = 74\%$. For this reason, the indicator for mining is heavily dependent on Codelco's responses due to the fact that the sample is small. Besides, foreign mining firms are not properly represented.

move closely and steadily around the neutral level of 50. Most of the time, entrepreneurs seem to be slightly more optimistic about the future than they are confident about their present situation. Instead, confidence in the national economic situation exhibits high variation over time.

Similarly, uncertainty about the present and future situation are more stable than uncertainty about the national economy. However, as one could expect, respondents tend to agree more about the national economic situation than on their own situation, which might be subject to idiosyncratic factors.

Figure 1

Confidence and uncertainty measures



Source: Authors' calculations using IMCE and IPEC data.

Table 1

Questions of interest in the IMCE survey – retail and manufacturing

Category	Questions
Present	How well will your sales/production evolve this month with respect to the previous one?
Future	How well will your sales/production evolve in the next three months with respect to the current level? How well will your business situation evolve in the next six months with respect to the current situation?
National	How well will the national economic situation evolve in the next six months?

Source: IMCE survey.

^{*} In this graph both uncertainty indicators have been standardized for the sake of comparison.



Table 2

Questions of interest in the IPEC survey

ersonal economic situation: is it better, worse, or the same as one year ago?
mily economic situation: will it be good, modest, or bad in the next 12 months?
ational economic situation: is it good, modest, or bad?

Consumer confidence: the IPEC survey

To analyze the effects of confidence on private consumption, we use data from the consumer confidence index, IPEC.⁶ The IPEC survey consults about 1,100 people about their perceptions of current and expected, personal and nationwide, economic situation. We focus on three such questions and compute confidence indicators following the same procedure we used to generate business confidence indicators from the IMCE survey. We list these questions in table 2. Questions 1) and 2) relate to the respondent's current and future economic situation, respectively, whereas number 3) relates to her perception of the national economic situation.

The bottom left graph in figure 1 presents the three measures of consumer confidence. Remarkably, consumers perceive their current situation consistently worse than the national economic situation, and below the neutral level. However, when asked about their future situation, consumers are generally optimistic, even during periods of economic downturns, such as 2009.

For the sake of comparability, it would be desirable to compute uncertainty indicators from the dispersion in the IMCE responses. However, we did not have access to the micro-data that was needed.

Economic uncertainty index

We complement our set of confidence and uncertainty indicators with the Economic Uncertainty Index (EUI), developed by Cerda et al. (2018), and made available on a monthly basis by Clapes UC⁷. This is a news-based index, which aims to capture the overall uncertainty in the Chilean economy. Relying on this indicator, they study the effects of uncertainty shocks on the Chilean activity.

The bottom right graph in figure 1 shows the economic uncertainty index alongside business uncertainty about the future. For the sake of comparison,

⁶ IPEC: Índice de Percepción de la Economía. The IPEC is currently collected by GfK Adimark (a private company) and comissioned by the Central Bank of Chile. It is available on a monthly basis since 2002.

 $^{7 \}quad \text{\'indice de Incertidumbre Econ\'omica. Available at https://clapesuc.cl/indicador/indice-de-incertidumbre-economica-iiec/}$

we standardize both indicators in this graph. It stands out a high correlation, between both uncertainty measures, even though both have constructed from completely different methodological procedures.

2. Cyclicality of confidence and uncertainty measures

In this subsection, we seek to document the empirical relationships between our expectation variables and cyclical measures of activity. In the first set of results, we look at pairwise cross-correlations between lags and leads of each variable. In the second, we perform Granger causality tests to assess whether our synthetic confidence indicators are useful for forecasting private expenditures and activity in general.

Cross-correlograms with activity variables

In table 2 we present the cross-correlations between lags and leads of investment and consumption with the confidence and uncertainty indicators. Negative numbers in the horizontal axis indicate the activity is leading confidence/uncertainty; conversely, positive numbers indicate that confidence/uncertainty is leading activity. Round markers indicate when the correlations are statistically significant at a 1% level.

We compare business confidence with investment in the top-left graph and consumer confidence with private consumption in the top-right⁸. In general, the highest—and statistically significant—correlations are obtained with leads of the confidence indicators. In this sense, these results suggest that confidence might lead investment and consumption. Investment growth correlates the most with confidence about the future situation, when confidence is leading by two quarters, and the correlation is statistically significant until six quarters. Likewise, consumption growth highly correlates with confidence regarding the personal future situation. This correlation peaks when confidence is leading by three quarters. Overall, these results are in line with the findings of Figueroa and Pedersen (2019), who examine the correlations between the IMCE and IPEC questions with GDP by sectors.

In addition, we observe an interesting relationship between consumption and present personal confidence: it is significantly positive when both are approximately contemporaneous, and significantly negative for long-range leads of present confidence. This pattern might indicate that consumers react to transitory income shocks: in the short term, they feel more confident and consume more, while in the long term, when the shock has dissipated, they must adjust their expenditure to their previous level of income.

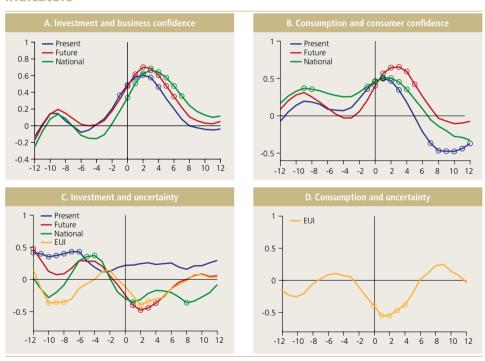
⁸ In this exercise, both investment and consumption are expressed in real year-on-year growth. All correlations are computed in quarterly frequency.



The bottom-left and bottom-right graphs of figure 2 present the same set of results for uncertainty indicators. In this case, the evidence is heterogeneous. For investment growth, the most negative correlations are observed when future uncertainty is leading activity, which is consistent with the empirical literature on the effects of uncertainty on investment decisions (e.g. Bloom et al. (2007); Bloom (2009)). Similar results are observed when we measure uncertainty using the EUI. However, when we look at the correlations with uncertainty about the future and the nation-wide situation, the pattern is less clear or harder to interpret. It is possible that the indicator of uncertainty about the present situation is more a measure of current disparity among firms, and thus need not to be correlated with activity. Finally, the bottom-right graph shows that EUI is a good leading indicator of private consumption. For example, if the EUI diminishes, then consumption tends to be higher.

Figure 2

Cross-correlograms between activity and confidence and uncertainty indicators



Source: Authors' calculations

Notes: Negative (positive) numbers on the horizontal axis imply that activity (confidence/uncertainty) is leading confidence/uncertainty (activity). A round marker indicates that the correlation is statistically significant when applying a 1% significance level.

3. Granger causality tests

To further explore how informative are synthetic confidence and uncertainty indicators to anticipate activity, we present evidence from Granger causality tests. As activity measures, we use total investment and two of its subaggregates: equipment and machinery and construction and infrastructure; private consumption and two of its sub-aggregates: durables and non-durables; and four lines of value-added GDP: manufacturing, construction, retail and financial and business services. We chose these sectors of GDP because they correlate the most with investment and consumption.

Table 3 presents *p*-values for the null hypothesis that confidence/uncertainty indicators do not Granger cause activity variables. Overall, business confidence indicators are useful to anticipate investment, consumption, and up to four lines of value-added GDP; consumer confidence indicators help anticipate consumption and two lines of GDP. Nevertheless, we cannot reject the null hypothesis that uncertainty indicators do not Granger cause activity variables.

A close look shows that confidence about the future robustly anticipates investment, consumption and GDP variables, with the only exception of durable-goods consumption, which does not pass the test at conventional confidence level of 5% (but do pass it at 10%). Also, entrepreneurs' confidence about the national economic situation has a reasonably good predictive power on activity, except for the value-added of construction. Therefore, these findings suggest that questions about the future and the national economic situation convey similar information. This is not surprising since confidence indicators capture a mix of judgments on past, current and expected economic developments. Finally, entrepreneurs' confidence in the present situation Granger causes investment and the added value of manufacturing, construction, and retail.

Consumer confidence indicators tend to be good predictors for consumption and the value-added of the manufacturing and retail sectors. It is also worth noticing that consumer indicators do not Granger cause investment expenditure variables.

Business uncertainty measures associated with the present and the national situation do not Granger cause consumption nor investment. However, there is evidence (at the confidence level of 5%) that uncertainty about the future does Granger cause total investment, its machinery and equipment component, as well as the value-added of manufacturing and financial and business services. For consumption and other lines of value-added, there is no systematic relationship of causation.

Finally, the economic uncertainty index seems to Granger cause private consumption and non-durable consumption, whereas we cannot reject no-causation for investment and value-added sectors.



Table 3

Granger causality in vars of pairs of variables (p-values)

H₀: Confidence indicators do not Granger cause activity variables

	Inve	Investment (GFCF)			Private consumption			GDP (1-digit sector)			
Rows Granger cause columns	Total	Equipment & machinery	Construction & infrastructure	Total	Non-durables	Durables	Manufacturing	Construction	Retail	Financial & business services	
A. Business confidence											
Present	0.006*	0.022	0.002*	0.482	0.238	0.585	0.009*	0.020	0.038	0.143	
Future	0.000*	0.002*	0.006*	0.002*	0.001*	0.058	0.000*	0.006*	0.004*	0.004*	
National	0.003*	0.002*	0.036	0.004*	0.002*	0.079	0.006*	0.251	0.016	0.006*	
B. Consumer confidence											
Present	0.204	0.656	0.106	0.001*	0.001*	0.318	0.016	0.321	0.055	0.398	
Future	0.564	0.519	0.070	0.003*	0.001*	0.004*	0.005*	0.075	0.010*	0.120	
National	0.132	0.255	0.083	0.002*	0.003*	0.028	0.009*	0.164	0.007*	0.205	
C. Business uncertainty											
Present	0.365	0.221	0.239	0.277	0.163	0.987	0.851	0.321	0.579	0.053	
Future	0.013	0.042	0.347	0.110	0.058	0.230	0.003*	0.593	0.092	0.039	
National	0.419	0.622	0.882	0.021	0.833	0.945	0.918	0.875	0.880	0.128	
D. Economic uncertainty											
EUI	0.272	0.343	0.749	0.044	0.029	0.125	0.105	0.606	0.223	0.419	

Source: Authors' calculations.

Notes: p-values for the null hypothesis of no Granger causality tested in bivariate VAR models with the number of lags selected according to the Schwarz information criteria. Bold numbers indicate rejection of the null when applying a 1% significance level. Activity variables are expressed in real year-on-year growth.

In table 4 we provide evidence in the other direction of causality, namely we test the null hypothesis that activity measures do not Granger cause confidence indicators. Overall, these results do not support reverse causation.

Table 4

Granger causality in vars of pairs of variables (p-values)

H₀: Activity variables do not cause confidence indicators

		Investment		Private consumption			GDP (1-digit sector)			
Rows Granger cause columns	Total	Equipment & machinery	Construction & infrastructure	Total	Non-durables	Durables	Manufacturing	Construction	Retail	Financial & business services
A. Business' confidence										
Present	0.059	0.438	0.005*	0.019	0.022	0.142	0.011	0.007*	0.184	0.517
Future	0.106	0.331	0.013	0.362	0.257	0.572	0.876	0.028	0.031	0.497
National	0.141	0.324	0.005*	0.118	0.069	0.379	0.001*	0.011	0.062	0.175
B. Consumer confidence										
Present	0.161	0.943	0.655	0.058	0.040	0.607	0.167	0.763	0.464	0.547
Future	0.039	0.038	0.525	0.124	0.080	0.217	0.585	0.338	0.192	0.801
National	0.971	0.740	0.918	0.320	0.340	0.895	0.572	0.701	0.744	0.959
C. Business' uncertainty										
Present	0.947	0.773	0.945	0.417	0.324	0.514	0.634	0.955	0.255	0.051
Future	0.623	0.884	0.033	0.005*	0.001*	0.050	0.348	0.098	0.059	0.388
National	0.078	0.056	0.008*	0.022	0.070	0.034	0.340	0.032	0.146	0.774
D. Economic uncertainty index										
EUI	0.308	0.294	0.297	0.243	0.325	0.186	0.341	0.689	0.210	0.919

Source: Authors' calculations. Notes: see note to table 3.

III. CONFIDENCE, UNCERTAINTY, AND ACTIVITY: DYNAMIC RELATIONSHIP

In this section, we present and discuss our main results. We examine the dynamics and propagation of activity resulting from structural innovations to confidence and uncertainty variables. In the first subsection, we briefly describe our empirical approach based on structural vector auto regressions. Then, we provide details on the variables and data transformations involved in our analysis. The following two subsections present the responses of investment and consumption to confidence and uncertainty shocks. The last subsection demonstrates two possible applications for our models.

1. Structural VAR approach

To assess the effects of confidence and uncertainty shocks on investment and private consumption, we use a multivariate setting. More precisely, we estimate a structural VAR (SVAR) with external (foreign) activity and financial shocks, and domestic expectations and activity shocks.



To account for Chile's small open economy features, we impose block exogeneity between external and domestic variables⁹. This condition assures that external variables do not respond to domestic shocks, while domestic variables respond to both foreign and domestic shocks. Thus, the SVAR model¹⁰ can be written as follows:

$$\left[\begin{array}{ccc} \boldsymbol{y}_{t}^{*'} \boldsymbol{y}_{t}^{'} \end{array} \right] \!\! \left[\begin{array}{ccc} A_{01} & \boldsymbol{0} \\ A_{03} & A_{04} \end{array} \right] = \! \left[\begin{array}{ccc} \boldsymbol{y}_{t-l}^{*} \boldsymbol{y}_{t-l}^{'} \end{array} \right] \!\! \left[\begin{array}{ccc} A_{11} & \boldsymbol{0} \\ A_{13} & A_{14} \end{array} \right] + c + \! \left[\boldsymbol{\varepsilon}_{t}^{*'} \boldsymbol{\varepsilon}_{t}^{'} \right],$$

where the $n\times 1$ vector y_t^* contains the endogenous variables for the external block, the $n\times 1$ vector y_t contains the endogenous variables for the domestic block (i.e., the small open economy), the matrices A_i and the constant vector are structural parameters. The zero blocks in the system reflect the block exogeneity assumption. Finally, the vectors ε_t^* and ε_t are the structural shocks and follow a Gaussian distribution with a mean of zero and variance-covariance matrix I_{n+n^*} (the identity matrix).

For the identification of the structural shocks, we use a Cholesky scheme. This identification scheme creates a recursive contemporaneous ordering among variables, where any variable in the vector $\begin{bmatrix} y_t^{*'}y_t^{\prime} \end{bmatrix}$ does not depend contemporaneously on the variables ordered after. Since it matters for the identification of structural shocks, we will discuss the ordering of the variables in the following subsections.

2. Data description and model specifications

External variables

Beginning with external variables that measure the global economic cycle, we consider two principal components and a proxy for the mining investment cycle. We define pc1 as the first principal component of a group of global-activity-related variables. This set includes various purchasing manager's index (PMI) measures, that track real activity of both emerging and advanced economies (including the US, European countries, China, Brazil, and a global compound) and real commodity prices (copper and oil relative to a trading partner's price index). 12

Next, we define pc2 as the first principal component of a group of global financial variables. This set gathers the Standard and Poor's stock market value index (S&P500), the asset's price volatility (VXO) and sovereign risk premium measures (EMBI) for Europe, Asia, Latin America, and a global average.

⁹ The block exogenity assumption in VAR models was first proposed by Zha (1999).

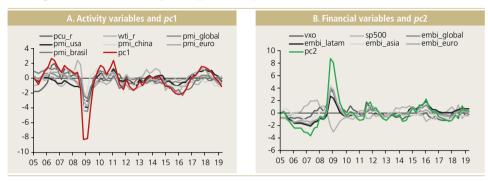
¹⁰ Further details on the model and estimation can be found in the appendix.

¹¹ This strategy follows Albagli and Luttini (2015). However, we separate external variables in a subset of real and in another of financial variables. Therefore, we end up with homogeneous variables in each group.

¹² PMIs report if business activity is expanding, remaining the same or contracting, according to firms' purchase managers.

Figure 3

Foreign variables and principal components



Source: Authors' calculations using data from Bloomberg and the Central Bank of Chile.

Figure 3 shows the evolution of standardized variables in each group. It is not hard to notice the high correlation between the original variables and the respective principal components. This correlation reflects that a large share of the variance is explained by these principal components: 62% and 76% for pc1 and pc2, respectively. Thus, we are confident that these two synthetic variables capture a relevant common movement between the whole set of external variables.

We also include in our set of external variables the Australian mining investment, as an exogenous instrument of Chilean mining investment. Our rationale is that the Chilean domestic mining investment cycle is highly correlated with the global mining investment cycle. In turn, this cycle responds to swings in commodity prices and whether investors perceived them as rather transitory or permanent (Fornero and Kirchner, 2018). This assumption is supported by García and Olea (2015), who found that Australia's mining investment behaves well as an instrumental variable for the mining investment cycle in Chile in the last decades.

Domestic variables

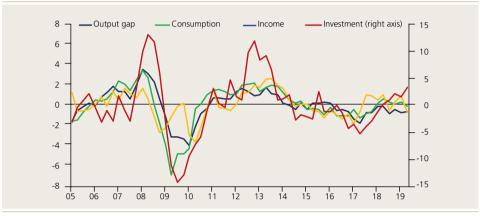
As domestic macroeconomic variables we include the output gap, real investment, real private consumption, and the real wage bill as a measure of aggregate real income (income, for short). All variables are expressed in logarithms and de-trended with the HP filter (Hodrick and Prescott, 1997). We present the resulting cyclical components in figure 4.



Figure 4

Output gap, private consumption, wage bill and investment

(cycle, %)



Source: Central Bank of Chile.

Model specifications

We estimate two specifications of the SVAR model outlined in section III.2: one for the analysis of investment, and another for consumption. This strategy allows us to better describe the dynamics of each demand component, while avoiding estimating a too large number of parameters.

Both models include seven variables. The SVAR with investment includes pc1, pc2, and mining investment in the external block. The domestic block considers business' confidence, business' uncertainty, the output gap, and investment. As measures of business confidence and uncertainty, we use the 'future' indicators presented in section II.

The SVAR with consumption also includes pc1 and pc2 in the external block, while the domestic block consists of consumers' confidence, economic uncertainty, the output gap, income, and private consumption. As a measure of consumers' confidence, we use the 'present' presented in section II, as it led to the highest explanatory performance in our multivariate setting. Since we do not have a consumer-specific uncertainty indicator, we use the economic uncertainty index, which we found to be a relatively good predictor of consumption (cf. subsection II.1).

The order we used to enounce the variables in the two previous paragraphs is the same ordering we establish in the models. That is, external variables go first, domestic expectational variables (confidence and uncertainty) go second, and domestic activity variables go third. Our decision to place confidence and uncertainty *before* activity is based on the evidence we found in section II (crosscorrelograms and Granger causality tests). However, as a robustness check, we

also estimate versions of the models where activity variables precede confidence and uncertainty indicators. 13

Both models were estimated using quarterly data in the sample period 2005.I-2019.II due to data availability. This sample period offers several the methodological advantages: we identify no structural breaks, the macroeconomic framework comprehends an inflation-targeting regime, exchange rate flexibility, an independent central bank, and a fiscal policy that follows a fiscal rule.

Both VAR models are of order one for two reasons. On the one hand, our sample contains 62 observations, while each model includes seven variables. Hence, the number of parameters of a second-order VAR would exceed the number of observations. On the other hand, both Schwarz's and Hannan-Quinn's information criteria support the selection of models with just one lag.

3. Empirical results

In this subsection, we focus on the effects of two structural shocks: (a) A 'confidence shock' that exogenously boosts confidence indicators. (b) An 'uncertainty shock' that exogenously increases the uncertainty index. We present the median response of investment and private consumption after structural shocks of size one-standard-deviation hit the economy. ¹⁴

Empirical results for investment

Figure 5 shows the impulse-response functions of investment after confidence and uncertainty shocks. The graph on the left presents the response to the confidence shock. During the first two quarters following the shock, investment increases by 0.5% over its trend level; in the mid-run, this shock has a relatively persistent effect that lasts about 12 quarters. Finally, in the long run, investment returns to its trend level.

The graph on the right shows the response to an uncertainty shock. One quarter immediately after the shock, investment falls by 0.8%, then it returns to its trend level after eight quarters. Overall, these results are consistent the international empirical evidence on the effects of uncertainty shocks (Bloom et al., 2007; Bloom, 2009) and with the 'wait-and-see' hypothesis, according to which higher uncertainty causes firms to temporarily pause investment, which in turn causes a rapid drop and rebound.

¹³ Since our measures of confidence and uncertainty correlate, our dynamic methodological approach controls for endogeneity as structural shocks are identified by imposing timing restrictions. Our baseline scheme assumes that uncertainty shocks do not affect confidence contemporaneously, but confidence shocks do affect uncertainty on impact. Alternative schemes, where this relation is reversed, and where one of these variables is taken out, yield similar results.

¹⁴ Median responses and standard error bands were estimated following a bootstrap procedure with 1,000 simulations.



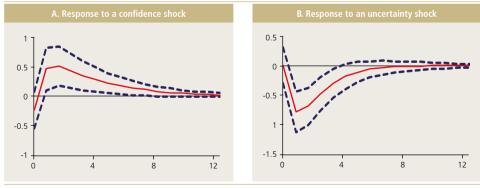
Our estimation of the response to an uncertainty shock is similar in shape and duration to Cerda et al. (2018)'s, who use a similar empirical framework. However, they find a much larger response of investment, of about -2.5% at its peak. Such a difference might come from the use of a different uncertainty measure, a different transformation to measure the cycle (they use real variables in year-to-year growth in comparison with us that define investment cycle), and/or the inclusion of other variables in the model.

Some comments on the findings. First, we notice that investment does not respond immediately to confidence and uncertainty shocks: on impact, the responses are close to zero, while as time passes the propagation yields non-zero effects. It is not trivial that the immediate impact is zero, since our specification allows all shocks to have a contemporary effect over investment. Second, these results are robust to the ordering of the variables; we find similar results when we impose that activity variables are not contemporaneously affected by confidence and uncertainty shocks (see appendix). Third, confidence shocks, in comparison with uncertainty shocks, have a more persistent, although less pronounced, effect on investment. This finding is consistent with the evidence that first-moment productivity shocks have persistent cyclical effects, while second-moment shocks have only temporary effects (Bloom, 2009).

What are the effects of these shocks on confidence and uncertainty indicators? After a one-standard-deviation confidence shock, the confidence indicator undergoes a steep increase of 9.4 points, which rapidly dissipates after four quarters. Business uncertainty decreases by 1.2 points on impact and quickly returns to its previous level. On the other hand, following an uncertainty shock, business uncertainty rises by 1.8 points and then returns to its original level after eight quarters. Confidence does not react by a significant magnitude.

Figure 5

Responses of investment to confidence and uncertainty shocks



Source: Authors' calculations.

Notes: Responses of investment to one-standard-deviation shocks. Dashed lines indicate one-standard-error confidence bands.

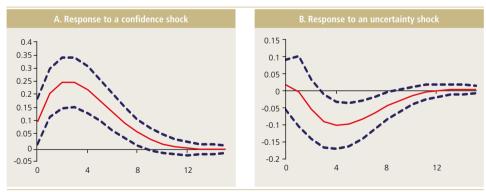
Empirical results for private consumption

Now we discuss the effects of confidence and uncertainty shocks on consumption. The left graph in figure 6 shows the response of private consumption to a confidence shock. Unlike investment, consumption does react on impact, with a median response of 0.1%. This response is sustained for two years after the shock, after which consumption returns to its trend level. The maximum response is only about 0.25%, half of the effect we found for investment.

The graph on the right presents the response to an uncertainty shock. We find that uncertainty shocks have an almost negligible effect on consumption: the most significant deviation from the trend level is only around -0.1%, by the first year after the shock. Moreover, this response is not statistically significant in most quarters. In contrast, Cerda et al. (2018) report larger effects, with a peak response of consumption around -0.6%.

What are the effects of these shocks on confidence and uncertainty indicators? After a consumer confidence shock, the confidence indicator rises by 3.0 points on impact and then gradually returns to the neutral level after 12 quarters. Economic uncertainty falls by 2 points and quickly reverses. In turn, following an uncertainty shock, economic uncertainty jumps 18.8 points and returns to its starting level after eight quarters. Consumer confidence exhibits a mild decrease of 1 point that lasts two years.

Response of private consumption to confidence and uncertainty shocks



Source: Authors' calculations.

 $Notes: Responses \ of \ private \ consumption \ to \ one-standard-deviation \ shocks. \ Dashed \ lines \ indicate \ one-standard-error \ confidence \ bands.$



4. Applications for policy analysis

In this subsection, we present two examples that demonstrate how our model can be useful for policy analysis. First, we look at the historical shock decompositions of consumption and investment to understand the determinants of recent demand fluctuations through the lens of the models. From this exercise, we conclude that external shocks might have a key role in explaining the Chilean business cycle, while the role of confidence and uncertainty shocks would be secondary. Second, we examine the responses of demand variables to external shocks (structural innovations to pc1 and pc2) and analyze how these might help in assessing the effects of global economic developments, such as the recent trade conflict between the United States and China.

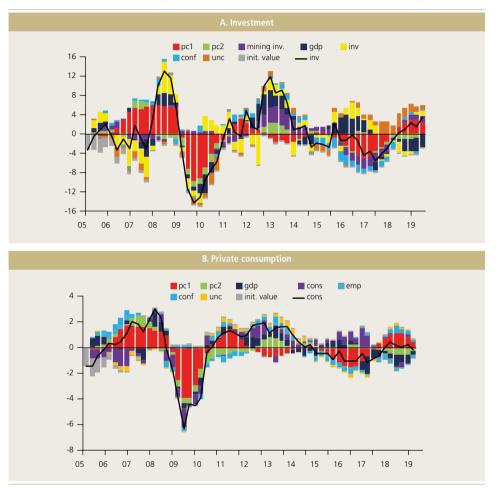
Studying cyclical fluctuations of consumption and investment

Figure 7 presents the historical shock decompositions derived from our SVAR models. These decompositions represent the contribution of each structural shock to the cyclical stance of the endogenous variables at any given time. We also compute these contributions as a share of the cyclical stance for the whole sample, and for five periods, which we present in table 5. We defined these periods according to the sign of cyclical investment and consumption.

The graph on the left of figure 7 shows the decomposition of investment. First, we notice that external shocks explain the lion's share of cyclical variation, and the main contributors are activity shocks (pc1), which explain approximately 40%. Mining investment shocks present significant contributions in two episodes: the boom of 2013 and the slowdown observed between 2014 and 2017, where it explains about one third of the investment cycle. Domestic shocks have contributed approximately 40% to cyclical fluctuations. In particular, confidence and uncertainty shocks have played a secondary role, with only 20% of the total contribution. However, we observe that confidence shocks explain an important share of the slowdown in investment seen in 2014-17 (approximately 38%).

The graph on the right shows the historical shock decomposition of private consumption. As investment, consumption is mainly explained by external shocks, which amount to 66% of the total cyclical stance. The contributions of confidence and uncertainty shocks are almost always procyclical, but they only explain about 16% in the whole sample.

Figure 7
Historical shock decompositions of investment and consumption



Source: Authors' calculations.

Notes: This figure presents the contribution of structural shocks to cyclical investment and consumption. Abbreviations: confidence (conf), uncertainty (unc), output gap (gdp), investment (inv), consumption (cons) and income (inc).

Assessing the effects of a decline in world activity

In the previous subsection, we showed that external shocks have had a major role in driving business cycle fluctuations in Chile. In this subsection, we examine more carefully the effects of an external activity shock and discuss what these results tell us about the possible impacts of a global economic slowdown on the Chilean economy.



Figure 8 presents the responses to a negative one-standard-deviation external activity shock. This shock decreases pc1 by 1.3 points on impact and has a persistent effect for about 12 quarters. The size of this shock is consistent with the recent evolution of external activity variables, in the context of the trade conflict between the U.S. and China. ¹⁵

The graph on the top-left and top-right show the responses of business confidence and investment, respectively. There is a significant fall in business confidence, of approximately four points, presumably, because entrepreneurs anticipate a weaker demand. This effect lasts about seven quarters. At the same time, we see a significant and persistent fall in investment, which peaks at -2% after the first year. At least two mechanisms could explain this reaction. First, a trade channel, according to which investment decreases because it is more expensive to import inputs such as equipment and machinery. And second, an expectations channel: entrepreneurs might become more pessimistic and uncertain about future demand, so they either adopt a wait-and-see strategy or stop projects right away.

Table 5

Contributions of structural shocks to cyclical activity

A. Contributions to cyclical investment (%)

Period	рс1	рс2	mining inv.	conf	unc	gdp	inv
2007.III-2008.IV	49	-8	-2	2	0	22	38
2009.I-2010.IV	59	13	-3	-1	13	16	-4
2011.I-2014.II	-10	13	34	16	7	34	7
2014.III-2018.I	76	3	34	38	-17	-29	-6
2018.II-2019.II	144	-49	50	16	105	-142	-24
2005.I-2019.II	38	4	15	11	8	9	12

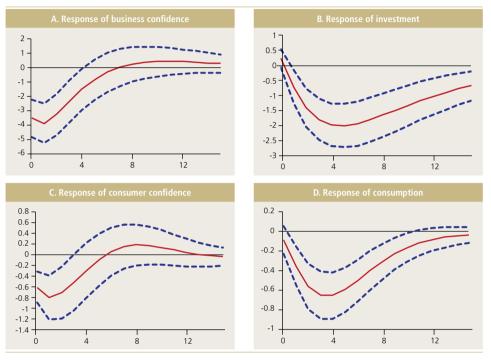
B. Contributions to cyclical consumption (%)

Period	рс1	рс2	conf	unc	gdp	cons	inc
2006.I-2008.III	84	24	18	-12	3	-18	7
2008.IV-2010.III	63	11	5	0	4	17	0
2010.IV-2014.IV	12	7	0	18	23	25	14
2015.I-2017.IV	99	-14	32	18	21	-68	11
2018.I-2019.II	371	-156	107	62	-196	-13	-75
2005.I-2019.II	60	6	10	6	5	4	5

Source: Authors' calculations.

Notes: This table presents the contribution of each shock as a share of the cyclical stance of investment and consumption. A negative value indicates that the shock contributed in the opposite direction during the respective period. The whole sample was divided into five periods were the cyclical investment and consumption change signs. Abbreviations: confidence (conf), uncertainty (unc), output qap (qdp), investment (inv), consumption (cons) and income (inc).

Responses of investment, consumption and confidence to an external activity shock



Source: Authors' calculations.

Notes: Negative (positive) numbers on the horizontal axis imply that activity (confidence/uncertainty) is leading confidence/uncertainty (activity). A round marker indicates that the correlation is statistically significant when applying a 1% significance level.

The bottom-left and bottom-right graphs present the responses of consumer confidence and private consumption. Consumer confidence exhibits a moderate fall of approximately 1.5 points, which reverts after five quarters. In turn, private consumption does not react immediately after the shock. We observe a decrease of 0.7% three quarters after the shock.

IV. CONCLUDING REMARKS

We have studied the effects of expectation shocks on aggregate private consumption and investment in Chile. We used microdata from the business climate survey IMCE and the consumer confidence survey IPEC to construct measures of confidence and uncertainty.

A bivariate analysis showed that these measures are useful for predicting activity up to six quarters ahead. Specifically, Granger causality tests showed that confidence might lead investment and consumption. Investment growth correlates the most with confidence about the future situation, when confidence



is leading by two quarters, and the correlation is statistically significant until six quarters. Likewise, consumption growth correlates the most with confidence in the personal future situation.

Then, using an open-economy SVAR approach, we identified confidence (first moment) and uncertainty (second moment) shocks. After a confidence shock, investment does not react on impact, but it exhibits a positive and persistent response in the 12 quarters following the shock. Private consumption shows a positive response on impact and returns to its trend level 8 quarters later. Uncertainty shocks generate a rapid slow-down and bounce-back in investment. Private consumption, instead, shows a weak negative response in the medium term.

REFERENCES

Albagli, E. and E. Luttini (2015). Confianza, Incertidumbre e Inversión en Chile: Evidencia Macro y Micro de la Encuesta IMCE, Central Bank of Chile.

Bachmann R., S. Elstner and E. Sims (2013): "Uncertainty and Economic Activity: Evidence from Business Survey Data." *American Economic Journal: Macroeconomics* 5(2): 217–49.

Bloom, N., S. Bond and J. Van Reenen (2007). "Uncertainty and Investment Dynamics." *Review of economic studies* 74(2): 391-415.

Bloom, N. (2009). "The Impact of Uncertainty Shocks." *Econometrica* 77(3): 623–85.

Cerda, R., Á. Silva and J.T. Valente (2018). "Impact of Economic Uncertainty in a Small Open Economy: The Case of Chile." *Applied Economics* 50(26): 2894–908.

Chanut, M. and C. Medel (2018). "Can Economic Perception Surveys Improve Macroeconomic Forecasting in Chile?" Working Paper No. 824, Central Bank of Chile.

Figueroa, C. and M. Pedersen (2019). "Extracting Information of the Economic Activity from Business and Consumer Surveys in an Emerging Economy (Chile)." Working Paper No. 832, Central Bank of Chile.

Fornero, J. and M. Kirchner (2018). "Learning about Commodity Cycles and Saving-Investment Dynamics in a Commodity-Exporting Economy." *International Journal of Central Banking* 14(2): 205–62.

García, P. and S. Olea (2015). "Inversión Minera y Ajuste Macroeconómico en Australia y Chile." Documento de Política Económica No. 56, Central Bank of Chile.

Hodrick, R. y E. Prescott (1997). "Postwar U.S. Business Cycles: An Empirical Investigation." *Journal of Money, Credit and Banking*, 29(1): 1–16.

Keynes, J.M. (1936). The General Theory of Employment, Interest and Money. New York, NY. Reprint 1964.

Lütkepohl, H. (2011). "Vector Autoregresssive Models." In: *Handbook of Research Methods and Applications in Empirical Macroeconomics*, edited by N. Hashimzade and M.A. Thornton. Cheltenham, U.K.: Edward Elgar Publishing.

Nowzohour, L. and L. Stracca (2017). "More Than a Feeling: Confidence, Uncertainty and Macroeconomic Fluctuations." Working Paper No. 2100, European Central Bank.

Zha, T. (1999). "Block Recursion and Structural Vector Autoregressions." *Journal of Econometrics* 90 (2): 291–316.



APPENDIX

DETAILS ON THE SVAR MODEL

The SVAR model can be written as follows:

$$\left[\begin{array}{c} \boldsymbol{y}_{t}^{**} \boldsymbol{y}_{t}^{*} \end{array} \right] \left[\begin{array}{ccc} \boldsymbol{A}_{01} & \boldsymbol{0} \\ \boldsymbol{A}_{03} & \boldsymbol{A}_{04} \end{array} \right] = \sum_{l=1}^{p} \left[\begin{array}{ccc} \boldsymbol{y}_{t-l}^{*} \boldsymbol{y}_{t-l}^{*} \end{array} \right] \left[\begin{array}{ccc} \boldsymbol{A}_{l1} & \boldsymbol{0} \\ \boldsymbol{A}_{l3} & \boldsymbol{A}_{l4} \end{array} \right] + c + \left[\boldsymbol{\varepsilon}_{t}^{**} \boldsymbol{\varepsilon}_{t}^{*} \end{array} \right],$$

where the $n^* \times 1$ vector y_t^* contains the endogenous variables for the external block, whereas the $n^* \times 1$ vector y_t contains the endogenous variables for the domestic block (i.e. the small open economy). The A_i matrices and the constant vector c are structural parameters, and p denotes the number of lags of the model. The zero blocks in the system reflect the block exogeneity assumption. Finally, the vectors ε_t^* and ε_t are the structural shocks and follow a Gaussian distribution with a mean of zero and variance-covariance matrix I_{n+n^*} (the identity matrix). The structural model may be written in compact form as:

$$Y_t' A_0 = X_t' A_+ + \xi_t'$$

by writing $Y_t' = \left[y_t^{*'}y_t'\right]$, $X_t' = \left[Y_{t-1}' \dots Y_{t-p}' 1\right]$, $A_+ = \left[A_1' \ A_2' \dots \ A_p' \ c'\right]$. The reduced-form VAR is defined as:

$$Y_t' = X_t'B + u_t'.$$

where $B = A_+ A_0^{-1}$, $u_t' = \xi_t' A_0^{-1}$ y $E[u_t u_t'] = \Sigma = \left(A_0 A_0'\right)^{-1}$. The reduced-form parameters B and Σ are obtained by OLS estimation of equation (2) and then an identification scheme must be adopted in order to identify the structural form (1).

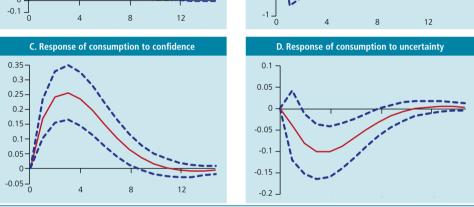
Several alternative methods are at hand for the identification of structural VAR models. In this work we will use a recursive identification scheme. We suppose that the variables in the vector Y_t are ordered from the most exogenous to the most endogenous. The the structural parameters can be obtained by Cholesky factorization of Σ .

Robustness checks

Order of the variables in the VAR

In figure A1 we replicate the results of sub-section III.3. using an alternative ordering for the variables. In the investment SVAR the ordering of the variables is the following: pc1, pc2, mining investment, output gap, investment, confidence and uncertainty. In the consumption SVAR we use the following ordering: pc1, pc2, output gap, income, consumption, confidence and uncertainty. Hence, our results are virtually equivalent to those exposed in the main section.

Figure A1 Responses of investment and consumption to confidence uncertainty A. Response of investment to confidence B. Response of investment to uncertainty 0.9 -8.0 0. 0.7 0.6 --0.2 0.5 -0.4 --0.4 0.3 -0.6 0.2 0.1 -0.8 0



Source: Authors' calculations.

-0.1

Notes: Responses of investment and private consumption to one-standard-deviation shocks. Dashed lines indicate one-standard-error confidence bands.